EVALUATING AND IMPROVING CORN NITROGEN FERTILIZER RECOMMENDATION TOOLS ACROSS THE U.S. MIDWEST

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Dedication

To

Heather, Evelyn, and Chloe.

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Abstract

Determining which corn (*Zea mays* L.) nitrogen (N) recommendation tools best predict the economically optimal N rate (EONR) would be valuable for maximizing profits and minimizing environmental consequences. The objectives of this research were to evaluate the performance of publicly-available N fertilizer recommendation tools across a wide range of soil and weather environments for 1) prescribing EONR for planting and split N fertilizer applications, 2) improve understanding of the economic and environmental impact of these tools, 3) improve N recommendation tools by integrating soil and weather information, and 4) improve N recommendation tools by combing multiple tools. The evaluation was conducted on 49 N response trials that spanned eight states and three growing seasons. Soil and plant samples, weather, and management information were collected using standardized procedures to allow for a side-by-side comparison of tools. Tool N recommendations were for fertilizer applications either at-planting or an inseason applied at V9 corn development stage.

Only 11of 31 tool recommendations were weakly related to EONR ($P \leq 0.10$ and $r^2 \leq 0.24$). These tools related to EONR resulted in only 21-47% of sites within ±30 kg N ha^{-1} of EONR. When considering partial profit for these 11 tools the average profitability relative to EONR range from -\$56 to -155 ha^{-1}. An environmental assessment of these 11 tools found there was no difference found between tools, with environmental costs ranging from -\$49 to 55 ha^{-1} relative to EONR.

Using an elastic net regression model to incorporate soil and weather information helped to improve six N recommendation tools. This improvement resulted in a stronger linear relationship with EONR ($r^2 \geq 0.20$ but ≤ 0.39; $P < 0.01$) and resulted in ≥ 35% but ≤ 55 % of the sites within ± 30 kg N ha^{-1} of EONR. Using other ways to improve tools

included combing two or three unique tools. The best results for an at-planting N fertilizer recommendation occurred when three at-planting N recommendation tools were combined with all interactions included in the elastic net regression model. This combined recommendation tool had an improved significant linear relationship with EONR ($r^2 = 0.46$; $P < 0.001$) compared with the best tool evaluated alone (an increase in r^2 of 0.27). The best combination of N recommendation tools for a split N fertilizer application occurred when using three tools with a decision tree ($r^2 = 0.45$; $P < 0.001$) over the best tool evaluated alone (an increase in r^2 of 0.18). However, while improvements to these publicly-available tools were noteworthy, over half of the variation in EONR was still unexplained. This was not surprising since many other factors that impact soil-crop N dynamics are unconsidered, including factors that occur after a sidedress N application.

Chapter 1: Literature Review and Objectives

INTRODUCTION

Nitrogen Use Efficiency

Nitrogen (N) is often the most limiting nutrient for economic corn (*Zea mays* L.) production. Nitrogen is essential for many physiological processes necessary in the crop's life cycle such as the production of amino acids, proteins, and nucleic acid. Without N, corn is unable to create chlorophyll, which directly affects carbohydrate production (Marschner, 2012). Extensive N deficiency in cornfields can result in stunted plants, yellow leaves, and drastic yield reductions (Lawlor et al., 2001).

Applying N as inorganic N fertilizer or animal manure can alleviate N deficiency. However, the N use efficiency (NUE), or amount of N recovered by the crop, has been estimated to be only 33% worldwide (Raun and Johnson, 1999). The low NUE is attributed to the many potential N loss pathways of the soil-crop system. These N loss pathways include denitrification, volatilization, surface soil runoff, leaching out of the rhizosphere, and gaseous plant emissions (Owens et al., 1995; Raun and Johnson, 1999; Eghball et al., 2003). Nitrogen lost to the environment often results in the degradation of water and air quality (Oberle and Bundy, 1987; Robertson and Vitousek, 2009; Reay et al., 2012).

To improve NUE, N supply needs to be better synchronized with corn demand (Shanahan et al., 2008; Walsh et al., 2012). There are several ways to better match N supply with corn N demand that are summarized in what is called the 4R guidelines of nutrient stewardship (right rate, right time, right source, and right place). Applying N at the wrong time has been considered one of the main reasons for poor NUE. The majority of N throughout the Midwest is applied at planting or before planting, such as in the fall (Cassman et al., 2002; Kitchen et al., 2008). Applying N prior to when there is a substantial crop need increases the potential for N loss. In contrast, applying N as close the V6 to V9 developmental growth stage where rapid N uptake occurs can allow for lower N rates while still maximizing yields (Walsh et al., 2012).

Applying N at the right rate is one of the most critical management practices farmers can implement to improve NUE. While it is not possible to achieve 100% NUE, applying less N fertilize improves NUE. Applying too little N fertilizer, however, will limit yields, while excessive N rates result in low NUEs. One method to optimize the N fertilizer applications is to apply N close to the economical optimal N rate (EONR), or the rate at which any additional N starts to decrease profitability. However, this is challenging due to the uncertainty of the EONR value for any given environment. This uncertainty arises due to the number of abiotic and biotic factors. One of these factors is the uncertainty of around how much N will be supplied by mineralization in a given season. Nitrogen mineralization is the process by which microorganisms breakdown organic-N to inorganic-N. Soils with sufficient mineralization can provide adequate N, so there is little or no response to N fertilizer applications (Cassman et al., 2002). This process varies spatially and temporally and is driven by soil total N, organic matter, soil texture, soil water content, drainage, topography, precipitation, temperature, and microbial activity (Schimel and Bennett, 2004; Lobell, 2007; Schmidt et al., 2007, 2011; Myrold and Bottomley, 2008; Tremblay et al., 2012). The high variability and uncertainty associated with many of these processes make it difficult to predict and incorporate into N management strategies.

Nitrogen Recommendation Tools

Yield Goal

To best aid farmers with N management decisions, many different N recommendation tools have been developed over the years. The earliest N recommendation tool resulted from research in the early 1970's that concluded that about 0.55 kg N ha^{-1} was needed to produce 25 kg ha^{-1} of desired corn grain (1.2 lbs N bu^{-1}; Stanford, 1973; Fig. 1). This research resulted in a yield-goal based N fertilizer rate calculation that was derived by taking this ratio multiplied by the desired yield goal for that field. This method could be referred to as a mass-balance approach to determining N rate. Several limitations of this method have been documented that show it often results in poor economic returns due to an over- or under-application of N when compared to the optimal N rate required to maximize yields (Fox and Piekielek, 1995; Kachanoski and Fairchild, 1996; Blackmer et al., 1997; Bundy et al., 1999; Lory and Scharf, 2003; Morris et al., 2018). This is especially the case in humid areas where inorganic N is highly susceptible to losses (Lory and Scharf, 2003). Nitrogen dynamics in humid regions are very complex and rely on interactions between tillage, drainage, soil organic matter, and weather (Dinnes et al., 2002). Of these factors, weather is hypothesized to have the greatest impact on driving N transformations and losses (Van Es et al., 2006). As such farmers have tended to over apply N as insurance during years of perceived high precipitation, resulting in yield-goal calculations to be inaccurate (Vanotti and Bundy, 1994).

The inaccuracy of yield-goal based recommendations are also a result of not accounting for differences in the NUE of different hybrid or fertilizer types, the amount of N supplied by the soil and miscalculating the obtainable yield (Vanotti and Bundy, 1994; Lory and Scharf, 2003). To better account for these perceived weaknesses, many state N fertilizer recommendations have changed by adjusting the factor by which yield goal is multiplied (Morris et al., 2018). In general, the variability of soil and yearly weather conditions are too high to make a reliable and consistent single N application based on these calculations. Furthermore, this method does not optimize economic returns for farmers since it is typically applied at a whole field basis; and as such, less productive parts of a field will receive more N then is needed (Fixen, 2006; Sawyer et al., 2006; Scharf et al., 2006).

PPNT and PSNT

The U.S. state experiment station programs began in the early 1980's to recommend that producers sample their soils for mineral N prior to fertilizer application to improve the yield-goal based recommendation (Magdoff et al., 1984; Fig. 1). High soil N concentrations could then be subtracted from the yield-goal recommendation, thus minimizing over application of N. Soil samples could be taken during the fall or just prior to planting when time allowed, hence the name pre-plant N test (PPNT). This test has been shown to be effective at reducing recommendations in fields that have high residual soil NO_3-N concentrations. High residual N in soil occurs when N is previously applied in excess of plant use or when manure is used in prior years (Bundy and Andraski, 1995). The PPNT test was also found helpful when used in conjunction with other management adjustments such as crediting a previous soybean (*Glycine max*) crop that reduces N fertilizer recommendation rates by a given amount (Scharf, 2001). Additionally, research has shown that PPNT is useful in medium- to fine-textured soils where the previous year's precipitation was normal or below normal and excessive N was applied (Gelderman and Beegle, 1998; Schröder et al., 2000). When soils remain wet for extended periods or when there is excessive rainfall on coarse-textured soils, the propensity for N-loss is high, and this test becomes less effective (Van Es et al., 2006). Furthermore, PPNT does not account for N made available through mineralization after the soil was sampled, which could result in over-fertilization (Schröder et al., 2000).

To guard against the potential loss of N that may occur during early vegetative growth stages, in-season N applications have been recommended (Magdoff et al., 1984). To accompany sidedress N applications, soil samples can be collected and tested for NO_3–N and be used to generate a fertilizer recommendation. This test has been called the pre-sidedress nitrate test (PSNT) and is utilized differently than the PPNT. Unlike the PPNT, the PSNT uses an index that is calibrated to crop N needs (Gelderman and Beegle, 1998). For example, when soil NO_3–N samples are taken before sidedress are above a defined high critical concentration, no additional N is recommended. If the concentration is below a critical level, then a full N fertilizer rate is recommended. However, any concentration between the high and low critical points requires a cutback on the total rate of N to be applied. There are slight differences in each state's critical points that guide when additional N should or should not be applied. Furthermore, each state has a different way of reducing the N fertilizer recommendation when N-values fall below the high critical point (Blackmer et al., 1997; Laboski et al., 2006). Not all Midwest states have a PSNT recommendation but instead, use either the Iowa PSNT method or methods that are available from neighboring states.

Compared to the PPNT, the PSNT provides a better estimate of the N supplying capacity of the soil (Gelderman and Beegle, 1998). Understanding the amount of N supplied by the soil during the season could further reduce the risk of over-fertilization of corn N need (Magdoff et al., 1984). This reduced risk of over-fertilization has been documented in research on fields where corn was grown following alfalfa or a manure application, where soil test results for PSNT had an increase of measured NO_3–N over the PPNT samples taken at the start of the study (Bundy et al., 1999). On sites with corn followed by corn and compared to PPNT, PSNT improved by 10% the number of sites that were predicted to respond to additional N fertilizer (Bundy et al., 1999). While shown to be an improvement over the PPNT recommendation, several limitations of the PSNT have hindered its expanded use. The main concerns being cost, additional labor, sampling difficulties due to wet field conditions, and having a short time window to obtain results from the lab before the data are needed to determine the N rate to apply (Schmidt et al., 2009).

MRTN

In more recent decades, N fertilizer recommendation tools have moved away from the yield-goal and soil-based strategies (Fig. 1). One tool that has replaced the mass balance approach in much of the U.S. Midwest Corn Belt is the Maximum Return to N (MRTN). The use of MRTN initiated in 2006 by a few Midwest states and has since expanded to include several surrounding states. The MRTN is based on hundreds of N response studies across different regions and crop rotation practices of the Midwest. An N recommendation for a given area and rotation is calculated by aggregating the N response trails based on soil or geographical boundaries. Each of the N response trials is fit with a function—linear, liner-plateau, quadratic, or quadratic-plateau. The best-fit function is used to determine the N rate that optimizes the return to N fertilizer inputs (RTN). This N rate changes based on corn and fertilizer prices, and the online MRTN database (nrc.agron.iastate.edu; verified 5 Mar. 2017) allows users to compare different prices. A final N recommendation is determined by averaging all of the calculated RTN together for that given region. Additionally, the MRTN recommendation provides a range of N rates that will produce a profit similar to MRTN (within \$2.47 ha^{-1}). This allows farmers to incorporate their level of risk in their decision-making process. Similar to previously discussed methods, the calculated MRTN can be credited for manure applications or residual soil NO_3–N levels measured prior to planting (Tremblay et al., 2012).

Comparison studies have found the MRTN approach to provide a more realistic measurement of EONR when compared to some of the established N fertilizer recommendation tools (Sawyer et al., 2006a). A comparison of seven sites in Illinois from 1999-2008 resulted in higher revenue using MRTN based calculations than corresponding yield-goal calculations (Febrer, 2014). However, MRTN, like many of the other N recommendation systems does not account for temporal or spatial N response variability (Morris et al., 2018). As such, MRTN will over-estimate EONR values from sites that are non-responsive and underestimate EONR for sites where excessive N loss occurs.

Crop Growth Models

Crop growth models have been developed to estimate crop growth by incorporating mechanistic and physiological processes. Recently these models have been utilized to provide an N recommendation to optimize corn yields (Setiyono et al., 2011). These models are more complex than the earlier discussed tools because they require detailed temporal and spatial information for many environmental and management factors. In contrast to previously mentioned tools where NUE was estimated and seldom changed, crop growth models are more flexible and account for additional variables to better estimate the NUE of a site and management scenario. For example, NUE is dependent on fertilizer types, N uptake, and the crop efficiency at converting acquired N to grain yield (Setiyono et al., 2011). This results in a less static method of predicting EONR for different farming situations and can better account for spatial and temporal variability.

The Maize-N model is one of a few crop growth models that combine these factors to predict a site's EONR. When validated it was found to better predict the actual sites' EONR over the Nebraska, Kansas, South Dakota, and Missouri yield-goal based calculations (Setiyono et al., 2011). Another study showed Adapt-N improved profits and reduced N rates compared to a farmer's N rate in 79, and 88% of the sites monitored, respectively (Moebius-Clune et al., 2013). Despite model tools being one of the latest developments (Fig. 1), improvements are still needed to make the computer-based algorithms more user-friendly and allow assumptions to be modified. This is especially true regarding making models more accurate across a broader range of soil and climatic environments (Sawyer, 2013).

Canopy Reflectance Sensing

Another tool that has been employed for making corn N fertilizer decisions is ground-based canopy reflectance sensing. Canopy reflectance sensing uses in-season measurements to assess the size (biomass) and color of plants to generate an N fertilizer recommendation (Kitchen et al., 2010). In this way, it is unlike the other tools since it uses very local and short-scale information (1-5 m) to provide N fertilizer recommendations (Raun et al., 2002). One of the advantages of this tool is the scale at which it works. The other tools listed above are used to recommend N fertilizer rate at a field scale or in the case of models at the scale that the soil resource is represented. Canopy reflectance sensing works at very short scales (< 5 m of row). These sensors work by emitting visible and near-infrared wavelengths and detecting reflected light energy from the crop canopy. In this way, it is using the crop plant as a bioassay of soil N availability. Measurements of corn needing N are compared to well-fertilized corn considered without N stress (Raun et al., 2002). The measurements are used to create indices, which when used with developed N algorithms provide a recommend amounts of additional N fertilizer that is needed (Dellinger et al., 2008; Solari et al., 2008; Franzen et al., 2016).

Canopy reflectance sensing has been used successfully to provide a variable N fertilizer recommendation on-the-go to address site-specific crop N needs. This is especially true when fields consist of high soil variability or when N could be limiting from variable N supply from manure, legumes, or high N loss from excessive precipitation (Kitchen et al., 2010). It can also work as a tool to improve crop N synchronization by applying N in-season and thus reducing the risk associated with N applications (Shanahan et al., 2008). This has been found in a study with 55 farm field trials which showed an average increase in partial profit of \$42 ha^{-1} relative to a fixed producer's N rate (Scharf et al., 2011). In other studies when used at a field scale with high soil variability, canopy reflectance sensors showed a profit increase between \$25 and 50 ha^{-1} when compared to a uniform N rate (Kitchen et al., 2010).

Improving Nitrogen Recommendation Tools

These tools briefly described for making corn N fertilizer recommendations have changed over time and by region. Their use has exposed their strengths and weaknesses (Morris et al., 2018). Today, farmers have many options to help determine the optimal N rates needed to maximize profit and reduce over-application and consequential N pollution in the environment. To help farmers improve their N management, these tools need to be validated and compared to determine which tools work best at estimating the EONR on fields of varying soil and weather conditions across the Midwest.

Tools that regularly generate wrong recommendations can be described as poorly performing tools; they need to be improved upon, or farmers should discontinue using them. Tools could be enhanced by allowing for in-season N management and account for spatial and temporal variability associated with EONR. The inclusion of soil and weather variation information could make these tools more sensitive to the wide range of corn-growing conditions across the U.S. Corn Belt, and thereby improve the overall accuracy of N fertilizer recommendations. This will significantly enhance farmers' options and their confidence in using these tools to meet their production needs and the public's need for reducing off-field losses of fertilizer N.

OBJECTIVES

The objectives of this research were to:

1. Evaluate the performance of publicly-available N fertilizer recommendation tools across a wide range of soil and weather environments for i) prescribing EONR for planting and split N fertilizer applications, and ii) improve understanding of the economic and environmental impact of these tools.
2. Identify the best statistical algorithm for selecting and incorporating soil and weather information into N recommendation tools to improve predictions of EONR.
3. Improve N management tools by adjusting N fertilizer recommendations with site-specific soil and current-season weather information.
4. Improve N management strategies by combining multiple N tools for a more robust N recommendation strategy.

DISSERTATION OVERVIEW

The overall goal was to compare and improve many of the publically-available corn N recommendation tools. Chapter 2 deals with comparing and contrasting these N recommendation tools for different objectives: 1) recommending N close to EONR, 2) partial profitability (Farmer's perspective), 3) environmental N loss (societal perspective), and 4) a combined farmer and societal perspective. Chapter 3 explores different statistical methods that could be used for improving N management tools by using site-specific soil and weather information to adjust the N recommendations. Chapter 4 utilizes the best statistical method determined from chapter 3 to improve many of the N recommendation tools. Lastly, chapter 5 looks at an alternative way to improve N management by combining different N recommendation tools ("tool fusion") as a way to better-estimated EONR.

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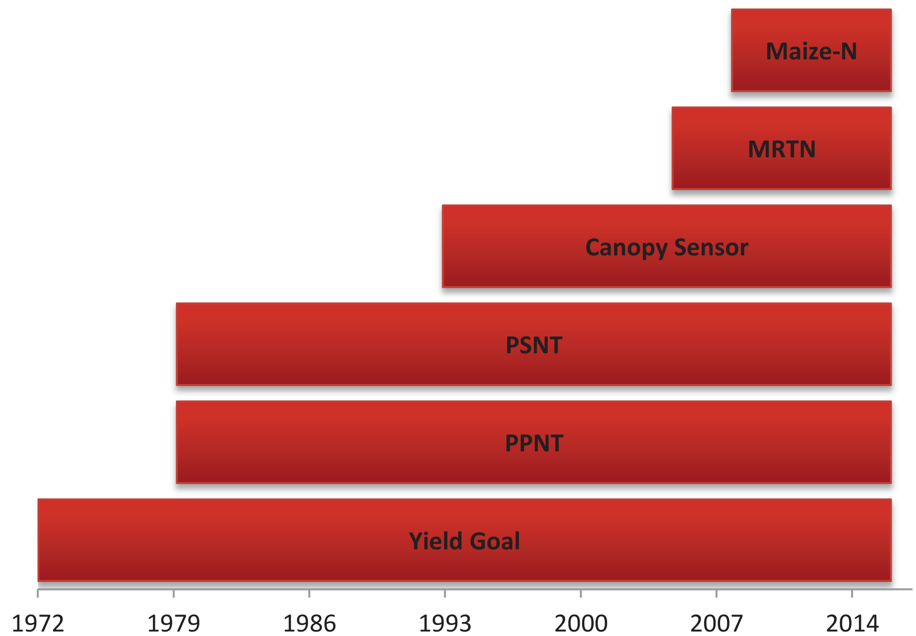

Fig. 1. Timeline of development and use of N management decision tools (Stanford, 1973; Magdoff et al., 1984; Rutto and Arnall, 2004; Schmidt, 2005; Fixen, 2006; Liu et al., 2015).

Chapter 2: Performance of Corn Nitrogen Rate Recommendation Tools Across the United States Midwest

ABSTRACT

Determining which corn (*Zea mays* L.) nitrogen (N) recommendation tools best predict the economically optimal N rate (EONR) would be valuable for maximizing profits and minimizing environmental consequences. The objectives of this research were to evaluate the performance of publicly-available N fertilizer recommendation tools across a wide range of soil and weather environments for 1) prescribing EONR for planting and split N fertilizer applications, and 2) improve understanding of the economic and environmental impact of these tools. The evaluation was conducted on 49 N response trials that spanned eight states and three growing seasons. Soil and plant samples, weather, and management information were collected using standardized procedures to allow for a side-by-side comparison of tools. Tool N recommendations were for fertilizer applications at-planting and when the majority of fertilizer applied as a top-dress (split) at V9 corn development stage. An environmental assessment was conducted by comparing an estimated inseason and post-season N loss at each tool's N recommendation relative to EONR. Total N loss was converted to an environmental cost using \$2.75 kg^{-1} NO_3–N. Results showed that only 11of 31 tool recommendations were weakly related to EONR ($P \leq 0.10$ and $r^2 \leq 0.24$). The 11 tools included the State-Specific YG used for split N applications, soil pre-plant and pre-side-dress soil nitrate testing (PPNT and PSNT) and canopy reflectance sensing. Furthermore, these tools related to EONR resulted in only 21-47% of sites within ±30 kg N ha^{-1} of EONR. When considering partial profit for these 11 tools the average profitability relative to EONR range from -\$56 to -155 ha^{-1}. In an

environmental assessment of 11 tools, there was no difference found between tools, with environmental costs ranging from -\$49 to 55 ha^{-1}. Also when combining both partial profitability and environmental costs, there were no differences between tools. While an N recommendation tool may perform well within a given year and U.S. state, these findings indicate current publicly-available N management tools mostly fail when applied across the broad environmental conditions represented by the U.S. Corn Belt, and further tool N recommendation tool development is warranted.

INTRODUCTION

Nitrogen is necessary for optimizing corn yields and is the most complex plant nutrient to manage. The difficulty of managing N in corn crop production is the result of the biophysical complexity driving soil N mineralization, crop uptake, and N loss (Meisinger, 1984, Lory and Scharf, 2003). This complexity is magnified as these processes vary considerably within and between fields because of spatial variability of soil properties and temporal variability associated with weather (Tremblay et al., 2012). Soil variability impacting the N cycle arises due to short- and long-range spatial differences in properties such as texture, organic matter, plant-available water, topography, and microbial populations (Parkin, 1987; Sørensen et al., 1995; Dinnes et al., 2002; Scharf et al., 2005; Zhu et al., 2009). Due to this complexity, farmers have to speculate how much N fertilizer to apply to achieve an optimal economic return. Since N fertilizer is typically inexpensive relative to the magnitude of crop response to this input, farmers often deal with this complexity and uncertainty by erroring on the side of over-application (Vanotti and Bundy, 1994). Applying N in excess of plant need decreases profitability and increases the potential for N loss that contributes to environmental degradation (Van Es et al., 2007; Maharjan et al., 2014).

Multiple N fertilizer recommendation decision tools have been developed in modern agriculture to help farmers be profitable with N management and minimize N loss from fields. An extensive review of the history, pros and cons, and current use of many of the corn N recommendation tools used within the United States has recently been contrasted by Morris et al. (2017). Many of the tools reported in Morris et al. (2017) are also included here in this investigation, as summarized in Table 1. Included tools are

1) mass balance calculations based on an expected yield or yield goal (YG), 2) pre-plant soil nitrate test (PPNT), 3) pre-sidedress application soil nitrate test (PSNT), 4) maximum return to N (MRTN) calculation, 5) Maize-N crop growth model, and 6) active optical near-plant canopy reflectance sensing.

One of the first methods for predicting N fertilizer rates was the mass balance approach developed in the early 1970's. Based on information about the N cycle and plant uptake, a value of 0.55 kg ha^{-1} of added N was estimated to produce 25 kg ha^{-1} of corn grain (1.2 lbs N bu^{-1}; Stanford, 1973; Table 2). This value multiplied by an area-based expected yield or yield goal produced the N recommendation. Limitations of this method have been documented showing that the YG and actual yield do not correlate well with EONR (Vanotti and Bundy, 1994; Fox and Piekielek, 1995; Kachanoski et al., 1996; Blackmer et al., 1997; Lory and Scharf, 2003). Furthermore, the YG approach has been noted to be more unreliable in humid areas where year-to-year mineralization of inorganic N as well as N loss in the environment is more difficult to predict (Lory and Scharf, 2003). Farmers have thus commonly applied more N than what was suggested by this tool to compensate for N loss that might occur during years of high precipitation, resulting in N applications considerably more than from the original YG recommendation (Vanotti and Bundy, 1994). The weakness of YG based recommendations have been attributed to not accounting for N use efficiency (NUE) of different hybrid or fertilizer types, the amount of N supplied by the soil, and poor estimation of yield (Vanotti and Bundy, 1994; Lory and Scharf, 2003). To account for these limitations, many state N fertilizer recommendations were modified merely by adjusting the coefficients within the YG equation. Even with these modifications, the variability associated with soil and weather interactions conditions are too difficult to predict and results in inconsistent performance of N fertilizer recommendations using this simplified mass balance approach. Most of the land-grant university fertility recommendation programs within the U.S. Corn Belt region discontinued in the 1990s and early 2000s N rate recommendations based on the YG approach (Morris et al., 2017).

To better address soil N contributions to the crop, other recommendation tools were developed that measure inorganic N before or during the growing season. The PPNT tool measures soil nitrate (NO_3–N) prior to planting as a credit to the N recommendation (Table 2). This test has been shown to be effective at reducing an over-application of N fertilizer in fields that have a large residual NO_3–N concentrations, such as excessively manured fields (Bundy and Andraski, 1995) or fields that experienced droughty conditions and significant unused N carried over from one year to the next (Meisinger et al., 2008). This test was also found helpful when used in conjunction with other considerations, such as giving an N credit following soybean (*Glycine max*) (Scharf, 2001). The PPNT tool performs best in medium- to fine-textured soils where the previous year's precipitation was average or below average and when excessive N was applied (Gelderman and Beegle, 1998; Schroder et al., 2000). In contrast, this tool is less useful when excessive rainfall causes either extended periods of ponding (fine-textured soils) or leaching (coarse-textured soils) promoting N loss to the environment (van Es et al., 2007). Moreover, since sampling occurs prior to planting, this tool does not account for N mineralization during the growing season, which could result in over-fertilization if in-season mineralization is high (Schroder et al., 2000).

A tool similar to the PPNT that incorporates in-season mineralization into its N recommendation is the PSNT (Table 1). Soil NO_3–N sampling for the PSNT tool is delayed four to six weeks after planting around the V5 developmental stage. The advantage of this tool is that the soil sampling and assessment is after the early growth stages of the crop when N demand is low and prior to when corn N uptake is much greater. The usefulness of this tool has been documented in research on fields where corn was grown following alfalfa or a heavy manure application; under these scenarios, soil test results for PSNT often showed an increase in NO_3–N levels when compared to the PPNT values (Bundy et al., 1999). While shown to be an improvement over PPNT recommendation in many situations, several issues related to the implementation of the PSNT have hindered its adoption (Table 1). Primarily, there are concerns with not being able to obtain soil samples due to possible wet field conditions. Additionally, farmers are reliant on soil laboratories to analysis and return PSNT values promptly under a narrow time frame between soil sampling and side-dressing N fertilizer (Schmidt et al., 2009).

Because of poor performance and implementation difficulties with YG and soil sampling tools, a more recent tool was developed called MRTN. The basis of this tool is an extensive database of field trials measuring corn response to N inputs (Sawyer et al., 2006). This free web-based tool determines an N recommendation using multiple N response models developed from over many years' trials and specific geographic regions, such as from a specific state or sub-region within a state. Nitrogen response models are fit to the observed yield from each trial. Trials from continuous corn are distinguished from trials where corn follows soybean. These response models are adjusted to include user-defined fertilizer and corn prices for calculating a localized EONR value to generate an N recommendation. To account for changes in climate and ongoing improved corn hybrids, MRTN database is updated with recent years' results and older years are removed. Similar to previously discussed methods, the calculated MRTN can be credited for manure applications or PPNT values (Laboski and Peters, 2012). Because the data used for the MRTN models span many years, recommendations from one year to the next for any given field will be consistent. A fairly constant recommendation is a weakness of this tool, as it does not account for the unique weather of a single growing season (Table 1).

With inexpensive data storage and management with cloud computing services, crop growth models that take into account all the major processes of the N cycle have recently been developed to produce N recommendations. These models use management inputs and site-specific soil and weather information to estimate soil N transformations and losses and plant physiological processes. Several crop growth models currently being used in the North American and the U.S. Midwest include Maize-N (Setiyono et al., 2011), Adapt-N (Melkonian et al., 2008), DuPont Pioneer's Encrica Services (www.pioneer.com/home/site/us/encirca; verified 10 Dec. 2017), Monsanto's FieldView Pro (www.climate.coml; verified 10 Dec. 2017), and Effigis' SCAN (http://www.effigis.com/en/solutions/scan; verified 12 Jan. 2018). The modeling approach for developing an N recommendation only became feasible with the advent of advanced computing power and information management as the models use high-resolution weather and soil information. This N recommendation method allows for a continual refinement based on additional field trails (He et al., 2017). A disadvantage of these tools is the costs required to obtain and incorporate new data into the model and maintain software. These costs must be passed on to farmers using it (Morris et al., 2017).

Other tools rely directly on light reflectance qualities of crop leaves to gauge crop N health and assist in making in-season N management decisions (Schepers et al., 1992; Scarf and Lory, 2002; Sripada et al., 2006; Scarf and Lory, 2009). For this investigation focus was given to proximal or near-plant active-optical canopy reflectance sensing (Dellinger et al., 2008; Holland and Schepers, 2010; Kitchen et al., 2010; Franzen et al., 2016). Active canopy reflectance sensors determine the crop's N status by assessing the size (biomass) and color of plants (Kitchen et al., 2010). This assessment works when sensors emit visible and near-infrared wavelengths and then detect specific wavelengths reflected from the crop canopy. These reflected wavelengths are used to develop vegetation indices, such as normalized difference vegetation index (NDVI) or normalized differences red edge index (NDRE). These indices are then converted into an N recommendation using one of many different publicly-available algorithms (Dellinger et al., 2008; Solari et al., 2008; Holland and Schepers, 2013; Franzen et al., 2016). In this way, canopy reflectance sensing is unlike the other previously described tools since they use very short-scale (1-5 m) information to provide N fertilizer recommendations (Raun et al., 2002). This tool has successfully identified plant N status and found in some studies to be a better predictor of EONR than soil-based tools (Gitelson and Merzlyak, 1995; Raun et al., 2002; Scharf et al., 2006; Scharf and Lory 2009). Drawbacks of this tool are the acquisition cost, the requirement for in-season N application, and the inconvenience of measuring or estimating [e.g., virtual N-rich reference (Holland and Schepers, 2013)] reflectance values from non N-stressed target corn.

An in-depth discussion of the rationale, strengths, limitations, and utilization of each of these tools for corn N rate decisions can be found in Morris et al. (2017). However, limited research has been done to compare simultaneously these tools over a wide range of soil and weather environments to determine their performance broadly. Previous studies that attempted to compare tools usually only focused on a small geographical area (e.g., within a state) and typically included only a limited set of decisions tools (e.g., a tool compared to the farmer's typical N rate). Furthermore, these studies often compared the tool's performance to each other, and not to a measured EONR. Without EONR one is only able to say which tool performs better, relative to another tool, but is not able to assess if the tool under- or over-recommended N, and by how much. Thus, there is a need for tools to be compared side-by-side and with EONR as the standard, over a wide range of soil and weather environments, to determine the accuracy and precision of each of these tools. Such an evaluation can lead to a better general understanding of the usefulness of N management tools when used over the U.S. Corn Belt.

The objectives of this research were to evaluate the performance of publicly-available N fertilizer recommendation tools across a wide range of soil and weather environments for 1) prescribing EONR for planting and split N fertilizer applications, and 2) improved understanding of the economic and environmental impact of using these tools.

MATERIALS AND METHODS

Experimental Design

This research was conducted as a part of a public-private collaboration between DuPont Pioneer and eight U.S. Midwest universities (Iowa State University, University of Illinois Urbana-Champaign, University of Minnesota, University of Missouri, North Dakota State University, Purdue University, University of Nebraska-Lincoln, and University of Wisconsin-Madison). Each state conducted research on two sites each year during 2014 to 2016, with a third site in Missouri in 2016, totaling 49 site-years. About half the sites were on farmers' fields and the other half on University research stations. All states followed a similar protocol for plot research implementation including site selection, weather data collection, soil and plant sample timing and collection methodology, N application timing, N source, and N rates, with specific details described in Kitchen et al. (2017). Treatments included N fertilizer rates between 0 and 315 kg N ha^{-1} applied either all at-planting or split where 45 kg N ha^{-1} was applied at-planting with the remaining fertilizer N applied at the V9 corn developmental stage.

Determining the Economic Optimal Nitrogen Rate

Grain yield in response to N fertilizer treatments was used to calculate the EONR on a site level as described in Kitchen et al. (2017), using proven quadratic or quadratic-plateau modeling methods (Cerrato and Blackmer, 1990; Scharf et al., 2005). Economic optimal N rate values were calculated for all N fertilizer applied at-planting (hereafter referred to as "at-planting"), and N split applied between planting and a single top-dress application (hereafter referred to as "split"). The cost of N was \$0.88 kg $N^{-1,}$ and the price of corn was \$0.158 kg grain^{-1} (equivalent to \$0.40 lbs N^{-1} and \$4.00 bu^{-1}). The EONR was set to not exceed the maximum N rate (315 kg N ha^{-1}). Five of the seven irrigated sites had N applied through irrigation > 12 kg N ha^{-1}, and this was included in determining the EONR of these sites. The EONR results were used as the standard for evaluating all other N recommendation tools. For 19 of the 49 sites, the at-planting and split EONR values were found statistically (P=0.05) to be same, within \$2.50 ha^{-1} of each other. Thus for these the EONR used was the average of the two timings. This approach was also consistent with previous separate analysis using this same dataset (Bandura, 2017).

Nitrogen Recommendation Tools Evaluated

Farmer's N Rate and Yield Goal

The farmer's historical N rate was the rate the farmer or research station typically applied to the field site under ideal corn growing conditions. The information the farmer/station manager used to derive this N rate was not determined, but it was assumed to be based on N response of the site over multiple years, and not necessarily on any specific decision tool.

Six YG tools were included in this evaluation as outlined in Table 2. These included a generic or general YG tool (General YG) based on original work of Standford (1973), four contrasting U.S. state-level YG tools [Indiana (IN) YG, Minnesota (MN) YG, Missouri (MO) YG, and Nebraska (NE) YG], and the state-specific YG (State-Specific YG) tool where sites within each state only used their respective state's YG method. Some states had a documented YG method that was the same or nearly identical to other states, and therefore these were excluded as individual tools in this evaluation, but they were included as a part of the State-Specific YG tool (see Table 2 for details). An exception was Wisconsin that was excluded from the State-Specific YG evaluation because it had no published YG tool. All YG methods follow a similar mass balance approach established by Stanford (1973), but each was uniquely modified by adjusting coefficients within the calculation and incorporating additional soil and management information (Table 2). For example, the Nebraska YG was adjusted with PPNT values that were either estimated or measured to a depth of 1.20 m. Each of these six YG tools was used to determine a corn N fertilizer recommendation for all 49 sites of this investigation.

All YG tools required an expected yield. The expected yield for each site was determined using the average of the previous five-yr county corn yields for the respective county the site was within. The five-yr average was then adjusted based on the soil productivity of the predominantly mapped soil of each site, similar to that done by Laboski and Peters (2012). This procedure classifies soil productivity as either low, medium, or high using soil texture, irrigation, depth to bedrock, drainage class, temperature regime, and available water capacity in the upper 150 cm of soil. The yield of a site was then calculated by increasing the five-yr average yield for low, medium, and high soil productivity by 10, 20, or 30%, respectively. This estimated yield value was used to represent the YG for the six different YG tools shown in Table 2.

Soil Nitrogen Tests

Four distinct PPNT tools were evaluated. They are as follows: 1) General PPNT, 2) MN PPNT, 3) North Dakota (ND) PPNT, and 4) WI PPNT (Table 2). Kitchen et al. (2017) detailed the sampling and NO_3–N analysis protocols for the PPNT tool. Two of the 49 sites did not complete PPNT sampling, so this tool was evaluated using 47 of the 49 sites.

Four PSNT tools were evaluated, including 1) General PSTN, 2) Iowa (IA) PSNT, 3) IN PSNT, and 4) WI PSNT (Table 2). These were tested under two different conditions; the first used a site average of measured NO_3–N from plots that received 0 kg N ha^{-1} at-planting. The second used a site average of measured NO_3–N from plots that received 45 kg N ha^{-1} at-planting. These are noted as PSNT 0 and PSNT 45, respectively, throughout this paper. Soil samples were taken at the V5 ± 1 corn development stage and to a depth of 0.30 m.

MRTN

The MRTN recommendation values for all sites were determined by using values obtained in 2016, as only a few states had updated the MRTN database during the three years of this project. The MRTN values for Iowa, Illinois, Indiana, Minnesota, and Wisconsin were obtained from the online Iowa state extension N rate calculator (cnrc.agron.iastate.edu; verified 5 Mar. 2017). The MRTN values for North Dakota were obtained from the North Dakota Corn Nitrogen Calculator (www.ndsu.edu/pubweb/soils/corn; verified 5 Mar. 2017). The price of corn to N fertilizer ratio used was 10:1. Since neither Missouri nor Nebraska currently have the compiled database and online tool for a MRTN recommendation, sites from these states were excluded from this tool's evaluation.

Maize-N Crop Growth Model

The Maize-N crop model version 2016.6.0 (Setiyono et al., 2011) was used in generating an N fertilizer recommendation for all sites. Required in-season weather data was obtained at each site using a HOBO (model U30) weather station (Onset Corporation, Bourne, MA). Weather data underwent a quality check and were then aggregated into a daily summary of minimum and maximum temperature, average solar radiation, and precipitation as explained in Kitchen et al. (2017). Additional historical weather data was required to generate an N recommendation. For this analysis, 30 years of site-specific weather data were obtained from DuPont Pioneer using a proprietary method for interpolating between multiple weather stations around each site. These weather data mostly came from public National Service Storms Lab (NOAA) weather stations, supplemented with data observed by DuPont Pioneer's internal weather network (HOBO stations). The weather data was collected within the acceptable range of 50 to 100 km radius as listed in the Maize-N user guide. Explicit information required by the Mazie-N crop growth model by each site included management records (e.g. date of planting, plant population, average historical yield, tillage operations, and previous crop) and soil information (e.g. bulk density, % organic matter, rooting zone depth, soil pH, and soil NO_3–N).

Canopy Reflectance Sensing

Canopy Reflectance measurements were obtained using the RapidSCAN CS-45 (Holland Scientific, Lincoln NE, USA) the same day or prior to the split N application. For the majority of sites, this was done at the ~V8-V10 corn development stage. Measurement details are described in Kitchen et al., (2017). The Holland and Schepers algorithm (HS; Holland and Schepers, 2010) was used to calculate an N fertilizer recommendation derived from these reflectance measurements. This algorithm is based on a sufficiency index calculated using measurements from both well-fertilized corn ("N-Rich") and minimally-fertilized corn that is referred to here as the "target" corn:

$$SI = \frac{VI_{Target}}{VI_{N-Rich}} \qquad [1]$$

where SI is the sufficiency index; VI_{Target} is the vegetative index obtained from averaging measurements from all plots that received 45 kg N ha^{-1} at-planting and where a top-dress fertilizer was to be applied, and VI_{N-Rich} is the vegetative index obtained by averaging all plots for two of the high N treatments (225 and 270 kg N ha^{-1} applied all at-planting). The NDRE vegetative index was calculated using the red-edge (730 nm; RE) and near-infrared (780 nm; NIR) wavelengths as shown:

$$NDRE = \frac{NIR-RE}{NIR+RE} \qquad [2]$$

Fertilizer N recommendations were then calculated as described in Holland and Schepers (2010) as follows:

$$N_{Rec} = \left(MZ_i * N_{Opt} - N_{PreFert} - N_{CRD} + N_{Comp}\right) * \sqrt{\frac{(1-SI)}{\Delta SI}} \qquad [3]$$

where N_{Rec} is the calculated N fertilizer recommendation; MZ_i is a scaling value ($0 \geq MZ_i \leq 2$) used to adjust the N recommendation based on areas of high or low yield performance; N_{Opt} was the base N rate, which is determined by the farmer; $N_{PreFert}$ is the amount of N already applied prior to sensing; N_{CRD} are N credits associated with the previous crop, NO_3–N in irrigation water, manure, or residual NO_3–N; N_{Comp} is an optional compensation factor for growth limiting conditions; SI is the sufficiency index, and ΔSI is a value to define the response range. For this analysis, MZ_i was left as the default value of 1.0, N_{opt} was set as the recorded farmer's N rate for each site, and $N_{PreFert}$ = 45 kg N ha^{-1}. With no supportive information relative to N_{CRD} and N_{Comp}, these two parameters were set to zero for all sites. The recommended value of 0.30 was used for ΔSI, which provides a response range between the measured vegetative index value between 0.70 and 1.00.

Statistical Analysis

Tools that could provide N fertilizer recommendations for both at-planting and top-dress applications were assessed with both timings and treated as two different tools. This separation of tools was warranted since for many sites N response and EONR results were different between the two N application times (Kitchen et al., 2017).

Two different metrics were used to evaluate the performance of each of the N recommendations tools across all sites. First, a tool's N recommendation was compared to the EONR across all sites using a simple linear regression model. Only if this relationship was positive and significant ($\alpha = 0.10$) was a tool considered successful and given any further evaluation. Additional evaluation included examining both the average and the RMSE of the difference between a tool's N recommendation and EONR. Using this approach tools were compared within a family of tools, between at-planting and split

N applications (when applicable), and across all tools and N application timings (average only). A second performance metric was to examine the percentage of sites a tool's recommendation came within ±30 kg N ha^{-1} of EONR. Sites within this range of EONR were considered reasonably close to EONR (RC-EONR). This value around EONR was chosen because it is about the same as what others have suggested as both reasonable and practicable for evaluating a tool's successful performance for generating an N fertilizer recommendation (Sawyer, 2013; Laboski et al., 2014; Sela et al., 2017).

Economic Assessment of Tools

To assess each tool from a profitability standpoint, a partial profit was calculated that included implementation costs (e.g., soil sampling, sample analysis, and procurement costs) and cost of N fertilizer and the corresponding yield revenue at each of the tool's N recommendation rates (Table 2). As such, each tool's partial profit relative to the EONR's partial profit was determined as follows:

$$Partial\ Profit = \left[(GY_{Tool} \times \$0.158\ kg\ grain^{-1}) - (N_{Tool} \times \$0.88\ kg\ N^{-1}) - IPC\right] - \left[(GY_{EONR} \times \$0.158\ kg\ grain^{-1}) - (N_{EONR} \times \$0.88\ kg\ N^{-1})\right] \quad [4]$$

where GY_{tool} and GY_{EONR} are the estimated yields associated with the tool's N recommendation and EONR, respectively; N_{Tool} and N_{EONR} are the N rates associated with a tool's N recommendation and EONR, respectively; and *IPC* is the implementation costs. The price of corn grain and the cost of N fertilizer was fixed at \$0.158 kg grain^{-1} (4.00 bu^{-1}) and \$0.88 kg N^{-1} (\$0.40 lbs N^{-1}), respectively. Corn grain yields were estimated using the same N response curves developed to calculate each site's EONR value. Implementation costs varied for each of the N recommendation tools based on the timing of N fertilizer application and the costs associated with sampling and analyzing soils as needed to implement the tool. Both the cost of N fertilizer applications and soil sampling were obtained from the Iowa Custom Application Survey (Plastina et al., 2017). The cost of analyzing the soil samples was calculated by averaging reported values obtained from five soil testing laboratories across the U.S. Midwest. An additional equipment cost was included in the canopy reflectance sensing analysis. All these implementation costs are described in Table 2. It is recognized that additional indirect costs for time and labor could be accrued that are related to completing forms, inputting information, and interpreting results. However, for this analysis, only direct costs required to obtain an N recommendation were used. This partial profit metric (Eq. 4) used to compare tools will always be negative unless a tool correctly predicts EONR at all sites and has no cost of implementation.

Environmental Assessment of Tools

An environmental evaluation for each tool was performed by accounting for both the N loss during the growing season as well as the potential N loss after harvest. Determination for each of these is described separately below.

For the in-season N loss during the growing season, an N balance procedure was calculated using known N inputs and removals. Thus this procedure did not attempt to identify N loss pathways. The approach used was as follows:

$$Inseason_{N\ loss} = (N_{Fert} + N_{Irr} + N_{Min} + PPNT) - N_{uptake} - N_{roots} - RSN \quad [5]$$

where N_{Fert} was the plot-level treatment N fertilizer rate; N_{Irr} was the inorganic N applied through irrigation; N_{min} was N that was quantified through an N mineralization test (Kitchen et al., 2017); PPNT was the pre-plant soil NO_3–N in the profile (0–0.90 m); N_{uptake} was the above-ground grain and biomass total N at plant maturity; N_{roots} was an estimated N content in the roots at plant maturity; and RSN was the post-harvest residual soil NO_3–N in the profile (0–0.90 m). Nitrogen mineralization was measured using the surface (0–0.30 m) PPNT soil samples with a 7-d anaerobic incubation procedure (Keeney and Bremner, 1966; Bundy and Meisinger, 1994). For the Nebraska 2015 and 2016 and North Dakota 2016 sites, no soil samples were preserved for N_{min}. For these sites mineralization values from nearby fields from other years of this study were used. The N_{uptake} was calculated as the product of the R6 developmental growth stage dry-matter mass for grain and stover samples and the total N concentration of these (Kitchen et al., 2017). To account for N immobilized by roots, N content was estimated using the measured shoot N content at plant maturity and using a root N to shoot N ratio of 0.20:1 (Crozier and King, 1993). The RSN was measured shortly after plot grain yield harvest. Samples were taken from every plot down to a depth of 0.90 m, separated and analyzed in 0.30 m increments.

Equation [5] was calculated for each plot within each site. A linear, quadratic, plateau-linear, plateau-quadratic, or exponential model was used to fit this calculated $Inseason_{N\ loss}$ for each site with both at-planting and split N application data. A model for each site was selected based on the assessed goodness-of-fit, the significance of the model, and the lowest RMSE (Table 5). The best-fit models for each site were then used to interpolate the $\mathrm{Inseason}_{N\ loss}$ associated with each N recommendation tool. A similar interpolated $\mathrm{Inseason}_{N\ loss}$ value was determined for each site's EONR value.

Potential N loss after harvest was defined as the RSN remaining in the soil after grain harvest. For calculating the potential N loss after harvest, a model selection procedure was conducted in the same manner as described above for $\mathrm{Inseason}_{N\ loss}$. These models could then be used to interpolate by site an RSN value to correspond with each tool's recommendation and EONR. To simplify the environmental assessment across soil and weather environments, all estimated RSN were considered lost to the environment.

A total N loss for each tool and EONR was calculated by adding the estimated $\mathrm{Inseason}_{Nloss}$ and estimated RSN values together (Fig. 1). The differences between these were monetized to create an environmental cost for using the tool as follows:

$$Environmental\ Cost = (N\ Loss_{Tool} - N\ Loss_{EONR}) \times \text{Prevention}\ Cost \qquad [6]$$

where N Loss_{Tool} and N Loss_{EONR} was the amount of total N loss calculated for each tool and EONR, respectively. The prevention cost for this analysis was determined to be \$2.75 kg^{-1} NO_3–N. This value was based on the average of previously reported implementations costs associated with reducing soil and water NO_3–N through various practices, such as drainage water management (Cooke et al., 2008), buffers and vegetative strips (Helmers et al., 2008), erosion control (Czapar et al., 2008), and cover crops (Kaspar et al., 2008). These costs were adjusted for inflation from their reported values to a 2015-dollar amount using an average inflation rate of 1.95% calculated using the FinanceRef inflation Calculator (www.in2013dollars.com; verified 15 Dec 2017). To simplify the environmental cost, the prevention cost was assumed the same for all reactive N forms lost to the environment.

Combined Economic and Environmental Assessment of Tools

Lastly, a total economic and environmental cost was calculated by adding results from Eq. [4] and Eq. [6] together (Fig. 1). Under certain conditions, it is plausible that the total combined profitability and environmental costs could ≥ \$0 ha^{-1}. A result of when a tool's relative environmental cost to EONR was much greater than the relative productivity, which would occur when a tool slightly underestimated EONR.

All calculations and analysis were conducted using the R Statistical Program (R Development Core Team, 2016).

RESULTS AND DISCUSSION

Nitrogen Response and EONR

In general, growing season precipitation at these research sites ranged from 245 to 1000 mm. Investigator observations noted few, if any, days of water deficiency stress with the corn crop. Still, given the varied soil environments represented across the 49 sites and excessive precipitation for some sites (Kitchen et al., 2017), a wide range of corn response to N fertilizer rates occurred. The EONR values across both application timings ranged from 0 and 315 kg N ha^{-1}. Of the 49 sites, three were nonresponsive to added N fertilizer, and another had an EONR value of less than 40 kg N ha^{-1}. In contrast, five sites resulted in high EONR values judged to be the result of excessive precipitation producing conditions of denitrification at sites with fine-textured soils and presumed leaching at sites with coarse-textured soils. For these sites, EONR values were at or near the highest N rate applied (315 kg N ha^{-1}). A summary of yield response to added N has been previously published (Kitchen et al., 2017). The average EONR was 169 and 159kg N ha^{-1} for at-planting and split N applications, respectively. The standard deviation of EONR across all of the sites was 83 and 70 kg N ha^{-1} for at-planting and split, respectively, demonstrating the extreme range of N response across sites.

Poor Performing Tools

Ideally, a successful tool would, first and foremost, have a significant positive linear relationship with EONR. Only when this condition was met was a tool judged successful in this assessment, and then other secondary metrics of performance were examined. These secondary metrics included average N rate recommendations relative to EONR, RMSE, and percentage of sites RC-EONR. The reason for the first linear regression examination as a screen is that averages alone can result in an incorrect assessment of tool performance. For example, a tool may on average produce an N recommendation close to EONR, but this could result from sites having N recommendations equally over-estimating EONR as sites under-estimating EONR.

A total of 20 of the 31 tools did not meet the first condition of being significant and positively related to EONR (see tools not bolded in Table 3). Note, many of the YG methods had a negative linear relationship with EONR (Table 3). No other tool produced N recommendations that were negatively correlated with EONR. The negative linear relationship indicates that these YG N recommendations overestimated EONR at lower N recommendation rates and underestimated EONR at higher N recommendation rates (Fig.

3). Not only was this negative, but the relationship was weak ($r^2 \leq 0.13$; $P \leq 0.02$), demonstrating that using a single YG method is not reliable for making N recommendations for the humid Midwest. Conversely, using the State-Specific YG for a sidedress N application was found to have a weak linear relationship with EONR ($r^2 = 0.10$; $P = 0.04$). This value was much lower than what others have also found for YG N recommendation tools ($r^2 \leq 0.21$; Blackmer et al., 1992; Vanotti and Bundy, 1994; Fox and Piekielek, 1995). Morris et al. (2017) summarized that YG based approaches are more suitable for irrigated corn production in arid environments where N mineralization or N loss varies little from year-to-year.

The majority of the tools were poor predictors of EONR with no significant positive linear relationship with EONR, including the Farmer's N rate, MRTN, and the Maize-N crop growth model. Many of the tools that did meet this first criterion of being successful were because the range of N recommendation was narrow relative to the range of EONR. The EONR values ranged from 0 to 315 kg N ha^{-1} and many of the tools N recommendations were between 98 and 283 kg N ha^{-1}. The poor predictability of EONR for many of these tools occurred because they did not adequately account for the N supplied by the soil. Due to substantial inorganic soil N, four of 49 sites were found to be nonresponsive to N fertilizer. Only two of these unsuccessful tools accounted for soil N supply during the season: the WI PSNT 45 and the Maize-N crop growth model. The WI PSNT 45 correctly identified two of the four nonresponsive sites but also falsely identified two sites as nonresponsive. The model was able to correctly identify two of the four nonresponsive sites for both at-planting and split N applications. However, the

Maize-N falsely identified five other sites for both at-planting and split N applications as nonresponsive.

To accurately predict if a site would be responsive or nonresponsive is difficult as it is influenced by management decisions, soil properties, and weather events that occur after an N application. The Maize-N crop growth model incorporates all of these parameters to estimate the N requirements of a corn crop and the N supplied by the soil through user inputs and in-season and long-term (≥10 yr) weather data. With the addition of actual in-season weather information, the Maize-N split N recommendation should, therefore, be more accurate at estimating EONR than when used for an at-planting application. However, for about half the sites (25 of 49) the split N recommendations were weaker predictors of EONR than the at-planting N recommendations. These results demonstrate that improvements are needed for the Maize-N model to better account for the year-to-year and location-to-location weather variability seen throughout the U.S. Corn Belt. Currently, many of the model coefficients used in Maize-N are simplified estimates of management, soil, and genetic parameters. These modeling parameters have shown to work well for the western Corn Belt, for which the model was developed, but additional changes to these coefficients may be one necessary step to improve the performance of the Maize-N model in other regions of the Corn Belt (Setiyono et al., 2011).

Since MRTN is promoted in six of the eight states participating in this research, further examination of why it was not related with EONR was warranted. The MRTN tool was developed from an aggregation of multiple site years of N rate response trials. This method provides a reasonable approximation of the EONR for a given region for which it was developed. However, this approach does not account for local variability due to temporal weather or spatial soil factors to N response (Morris et al., 2017). The observed EONR in this study ranged from 0 to 315 kg N ha^{-1} while the MRTN recommendations were between 129 to 228 kg N ha^{-1} (Fig. 2a). Across all the environments included in this research, MRTN on average came close to EONR (Table 4), but this was due to an equal number of N recommendations overestimating as well as underestimating EONR (Fig. 6). Nevertheless, MRTN could be a good starting point for N management decisions. Its prediction can be improved when incorporated with a PPNT tool, as seen in Fig. 2b where it was used as part of the WI PPNT.

Although the tools previously discussed were considered to perform poorly, information of their performance is included in all figures and tables. However, additional discussion will focus only on tools that had a significantly positive linear relationship with EONR. For convenience, successful tools meeting this first criterion are bolded or highlighted in the tables and figures.

Successful Tools

Only 11 of 31 were tools judged to be successful in making N fertilizer recommendations (see bolded in Table 3). For tools making N recommendations at planting, only 3 of 13 met this first condition. For tools making N recommendations for split applications, only 8 of 18 tools were found successful. Success was found with using the State-Specify YG at sidedress, three of the four PPNT tools, six of the eight PSNT tools, and canopy reflectance sensing. At the same time, no tool produced a recommendation rate that closely matched EONR, with the best-observed linear model producing a relatively low coefficient of determination (r^2 =0.24; P <0.001; for IA PSNT 0; Fig. 2c). Lack of performance was also considered to be less than ideal when examining RMSE values (Table 4); the best tool (IA PSNT 0) and worst (General PSNT 0) tools relative to RMSE gave values of 68 and 92 kg N ha^{-1}, respectively.

State-Specific YG

When each state utilized their respective YG method for a sidedress N recommendation, there was a significant and positive linear relationship with EONR. The improved performance of utilizing the State-Specific YG at sidedress over the at-planting N application timing occurred due to lower sidedress EONR values and all NE sites reducing their YG-based N recommendations for the sidedress application time by 5%. While not all of the other states recommended an adjustment based on application timing, what adjustment was made by the NE sites was enough to make this tool successful. Further improvements for all other YG methods could be made by implementing a similar reduction based on application timing.

Pre-plant Soil Nitrate Tests

Three PPNT tools produced N recommendations related to EONR (General, MN, and WI), but these tools explained no better than 16% of the variability in EONR (P ≤0.01; Table 3). These tools work by adjusting a base N recommendation (State-Specific YG or MRTN). By themselves, the base N recommendations overestimated EONR, but after adjusting for PPNT measurements the General, MN, and WI PPNT tools underestimated EONR by an average of 40, 26, and 5 kg N ha^{-1} (Fig. 4; Table 4). These

PPNT N recommendations improved over the base N recommendations because measured NO_3–N was subtracted from the base N recommendation. As such, these PPNT tools were effective at adjusting sites that overestimated EONR.

Of the three PPNT tools judged successful, the WI PPNT performed best. While this tool was not statistically significantly different from the other PPNT tools (Fig. 7), it underestimated EONR by only 5 kg N ha^{-1}, and the RMSE was 14 and 9 kg N ha^{-1} lower than the General and MN PPNT, respectively (Table 4). Furthermore, the recommended N rate from the WI PPNT tool had 34 % sites RC-EONR compared to 21 and 32% of sites for the General and MN PPNT, respectively (Table 4). The improved performance of this tool was in part because the WI PPNT accounts for background NO_3–N levels but does not recommend adjustments if the PPNT results are below 56 kg N ha^{-1} (Table 2). Due to low PPNT values measured across environments, no adjustment to the base N recommendation (MRNT) was made for 22 of the 44 sites evaluated (Fig 2a and 2b). However, for 8 of those 22 sites, an adjustment would have been beneficial as the base N recommendation overestimated EONR by as much as 30 kg N ha^{-1}. Another reason for the improved performance of the WI PPNT over the other two PPNT tools was that the WI PPNT adjustments were more substantial as it accounted for NO_3–N levels down to 1.20 m rather than 0.60 m. This improved the final WI PPNT recommendation for those nonresponsive sites over the other two PPNT tools (Fig 2a and 2b).

One factor of this study that may have reduced the predictability of PPNT N recommendations was that many of the study sites were corn following a soybean crop. Soybeans have been shown to be an excellent scavenger of soil NO_3–N; resulting in a minimal amount of NO_3–N remaining in the soil the following spring (Shapiro et al., 2008; Kaiser et al., 2016). The PPNT may be better suited for conditions where residual soil NO_3–N would accumulate, such as with manured fields.

Pre-Sidedress Soil Nitrate Test

The PSNT tools performed better when evaluated under the conditions of 0 kg N ha^{-1} applied at-planting compared to when 45 kg N ha^{-1} was applied at-planting (Fig. 5). Of the PSNT methods evaluated with 0 kg N ha^{-1} applied at-planting, the General, IA, and WI PSNT tools were significantly and positively related to EONR. These tools performed similarly as their average recommendations were close to EONR, the RMSE deviation from EONR, and the percentage of sites RC-EONR (Table 4). While the IA PSNT 0 tool underestimated EONR by ~20 kg N ha^{-1} more than the other tools, its predicted N rate had the best linear relationship with EONR ($r^2 = 0.24$, $P < 0.001$) of all N recommendation tools assessed (Table 3, Fig. 2). Nevertheless, this relationship with EONR was not particularly strong and substantially less than what other researchers have reported for other PSNT tools. Schmidt et al., (2009) reported the Pennsylvania PSNT to have an $r^2 = 0.48$ with EONR. The relatively weak relationship found here with the tools used in this multi-state study compared to other studies could be related to the large geographic area and variability in weather from year to year. This would suggest that these PSNT tools are not well adapted for sites with extreme environmental differences. A similar finding was documented in Scharf et al. (2006) where pre-sidedress NO_3-N concentrations from 62 sites across seven Midwest states had a weak relationship with the optimal N rate ($r^2 = 0.16$).

Of the four PSNT tools evaluated with 45 kg N ha^{-1} applied at-planting, the General, IA, and IN tools were found to be related to EONR. Of these tools, the IN PSNT 45 had one of the lowest RMSE and on average came closest to EONR (Table 4). The IN PSNT differs from the other PSNT methods as the N recommendation is categorized into six groups of N rates based on expected yield (Brouder and Mengel, 2003). While this method had a significant relationship when 45 kg N ha^{-1} was applied at-planting, no significant relationship was observed with EONR when evaluated with 0 kg N ha^{-1} applied at-planting. The reason for the lack of consistency between the IN PSNT tools with the different N rates applied at-planting N amounts is unknown.

One explanation for why the PSNT 45 tools further underestimated EONR was that the added 45 kg N ha^{-1} masked the N-supplying capacity of the soil. Others have found limits as to how much N could be applied at-planting before the PSNT becomes ineffective in predicting N requirements. Fernández et al. (2009) stated that the PSNT tool should not be used if > 22 to 30 kg N ha^{-1} was applied at-planting, while Blackmer et al. (1997) reported a limit < 84 kg N ha^{-1}. Additionally, Ketterings et al. (2012) documented the limit to be < 45 kg N ha^{-1} when fertilizer was banded. It is evident from this research that 45 kg N ha^{-1} applied at-planting reduced the effectiveness of the PSNT tools.

The PSNT is not currently advised under certain situations, such as sandy soils or soils with low organic matter (Fox et al., 1989; Meisinger et al., 1992). Nevertheless, removing the three sites with sand >80 % from the analysis resulted in a little or no improvement for all of the PSNT tools (reduced RMSE < 5 kg N ha^{-1}; data not shown). As such, all sites were included in this analysis regardless of soil texture.

Canopy Reflectance Sensing

The recommended N rate from the canopy reflectance sensing had a significant but weak linear relationship with EONR ($r^2 = 0.13$; $P = 0.01$). On average canopy reflectance sensing underestimated the amount of N required by 49 kg N ha^{-1}, which was the most of any of the 11 successful tools (Table 4 and Fig. 6). The N recommendation from the canopy reflectance sensing resulted in only 22% of sites RC-EONR. This was comparable to the Maize-N model and the majority of YG recommendations used for split applications (Table 4 and Fig. 6). The relatively poor performance of canopy reflectance sensing at many sites was a result of the minimal differences between the N-Rich plots and target plots (SI values averaged 0.93). For the majority of sites, the corn that received 45 kg N ha^{-1} at-planting (target plots) produced reflectance readings very similar to the N-Rich plots. When SI values are high, the algorithm decreases the N recommendation, which with this dataset often resulted in underestimating EONR. Using the same 49-site dataset, Bean et al. (2018a) showed that sensing plots that received 0 kg N ha^{-1} at-planting improved the performance of the tool slightly over sensing plots that received 45 kg N ha^{-1} at-planting. Similar results were observed in another regional dataset, which showed the HS algorithm on average underestimated the optimal N rate, resulting in significant yield loss compared to a high N reference for four of 11 sites (Thompson et al., 2015).

Efforts to improve canopy reflectance sensing with this dataset (49 sites) showed some promising results. Using a different algorithm developed in Missouri, Bean et al. (2018a) showed improved performance, as the numbers of sites RC-EONR were as high as 39%. However, this improvement still did not match the performance of the PSNT tools where the number of sites RC-EONR was ≥ 41% (Table 4).

Economic and Environmental Impacts of Tools

Partial Profitability

Partial profit between the planting and split N application timing tools showed no difference ($P = 0.43$; Fig. 8). As such, all tools used for both timings were illustrated together (Fig. 8). When comparing all successful tools (significant and positively related to EONR) collectively, significant differences were found between tools (Fig. 8). The General PSNT 45 had the lowest partial profit and was significantly different from the General PSNT 0, State-Specific YG, and WI PPNT tools ($P \leq 0.05$; Fig. 8). Apart from these differences, all other tools were not considered significantly different from each other.

The interpretation of these results demonstrates the opportunity cost associated with tools that are unable to predict an N rate that matches EONR. With just the 11 tools found related to EONR, the average partial profit was -\$91 ha^{-1}. Though both the N recommendations differing from EONR and the tool implementation costs are included in this analysis, the former generates the majority of the negative partial profit (Table 2). While unrealistic to think any tool could generate an N recommendation equivalent to EONR all the time, clearly this analysis provides a message of economic opportunity for having tools that are better at predicting EONR.

For farmers to adopt N recommendation tools, they need to be affordable, simple to use, and profitable. Much of N for the U.S. Midwest is currently applied to corn in the fall or early spring before planting because of convenience and available time. To compensate for the convenience of applying N early, tools that are reliant on soil/plant information need to perform equally if not better than fall applications. Furthermore, while tools tailored for in-season N fertilizer applications allow farmers the convenience of focusing more on planting operation concerns, it also requires application equipment capable of covering many acres within a narrow time frame.

Environmental Assessment

The relationship between $\text{Inseason}_{\text{N loss}}$ and fertilizer N rate differed across sites (Table 5). For 43 of 49 sites, $\text{Inseason}_{\text{N loss}}$ increased with increasing N fertilizer rates. However, 7 of the 49 sites showed no change in N loss while increasing N fertilizer for both at-planting and split applications (Fig. 9). The RSN was found to have no change with increasing N fertilizer rate for 2 out of 49 sites. The type of response function that best fit $\text{Inseason}_{\text{N loss}}$ or RSN varied by site and application timing (Table 5).

The estimated total N loss ($\text{Inseason}_{\text{N loss}}$ + RSN) at EONR resulted in an average and standard deviation across all sites of 136 (± 90) and 137 (± 84) kg N ha^{-1}, for at-planting and split applications, respectively. Moreover, the corresponding average and standard deviation of environmental costs were \$152 ha^{-1} (± \$101 ha^{-1}) and \$153 ha^{-1} (± \$93 ha^{-1}) for at-planting and split applications, respectively. In comparison, sucessful tools on average resulted between –\$49 and 55 ha^{-1} relative to EONR (Fig. 9; Table 4). A positive cost indicates that a tool's N recommendation resulted in reduced N loss compared to EONR, because of under-estimated crop N needs, and thus acting as an environmental credit.

When comparing all successful tools with each other, there was no significant difference found. This is not surprising as Hong et al. (2011) and Bandura (2017) showed that there was no significant increase in RSN until N rates exceeded EONR by about 30 kg N ha^{-1}. As none of the well-performing tools' recommended an N rate in excess of EONR by more than 21 kg N ha^{-1} (Fig. 7), there was no expected significant difference for total N loss between these tools.

Combining Economic and Environmental Costs

No differences were found between the previously identified successful tools when the partial profit and environmental costs were combined (Fig. 10). This occurred because the tools that had a poor partial profit due to underestimating EONR (e.g., General PSNT 45 and canopy reflectance sensing) had a higher environmental "credit" which helped to balance the total combined economic and environmental costs. Tools based on soil sampling (PPNT and PSNT) tended to have a combined economic and environmental cost closer to EONR. As previously stated when partial profit was discussed (Fig. 8), the results displayed in Fig. 10 give a better understanding of the relative opportunity costs associated with the tools assessed, however in this case both farmer (profit) and public (environment) interests are represented.

The combined costs associated with each of these tools could change depending on the prices used to calculate profitability and environmental costs. The environmental costs are more likely to change than the partial profitability as they vary widely in the literature. An evaluation of management practices to reduce N loading in the environment, resulted in values between \$3 to 57 kg N^{-1} yr^{-1} (Christianson et al., 2013;

Zhang et al., 2015). These costs could increase by a factor of ten or more if the cost of using water treatment facilities to remediating NO_3–N were included in the analysis (Jensen et al., 2012). Using different costs would not change the comparison between tools, but the magnitude of differences would be larger than what is reported here.

As concerns with environmental issues associated with N fertilizer continues to increase, social pressures may limit N management options for farmers. Some of these options would be to apply less N during the fall and more in the spring or top-dressed (Scharf et al., 2002; Christianson et al., 2012). Another option would be to reduce N rates applying more N in-season rather than at-planting (Christianson et al., 2012). In this case, the PSNT tests and canopy reflectance sensing would be ideal tools, but their adoption is hindered by implementation logistics. Using a higher environmental cost would further promote the use of canopy reflectance sensing, as it had one of the highest environmental credits. In comparison to the PSNT tools, canopy reflectance sensing is easier to use and applies N at a higher spatial resolution, close to a plant-by-plant basis. This higher resolution N application allows for adjustment to account for landscape positions or parts of the field that are more prone to runoff or leaching. Additional improvements to this tool could be incorporated using site-specific soil and weather information, allowing for a more adaptive N recommendation tool (Bean et al., 2018b).

CONCLUSIONS

There are many N recommendation tools available to aid farmers in improving N management. No N recommendation tool worked well for all growing conditions. Only 11 of the 31 tools evaluated were considered successful tools as they were significantly and positively correlated with EONR ($r^2 \leq 0.24$; $P \leq 0.07$). The successful tools were based on soil sampling (PPNT and PSNT) and canopy reflectance sensing. Of these tools the WI PPNT and General PSNT 0 had some of the better profitable returns; however, there were minimal significant differences between all the successful tools. From an environmental standpoint, none of these successful tools were significantly different from each other. When combining the partial profitability and environmental costs associated with each tool, none of the successful tools stood out. However, as environmental costs increase, tools that underestimate EONR would counterbalance any loss in profitability.

This side-by-side comparison of these tools shows that no one tool is best for any one environment. Tools that are adaptive and more responsive to soil and weather information for generating an N recommendation could improve the performance of tools. Additionally, some of these tools could be utilized together to form a new N recommendation approach, in such a way the strengths of multiple tools could be leveraged for better corn N management.

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Table 1. Strengths and weaknesses of N fertilizer recommendation tools included in this investigation (YG, yield goal; PPNT, pre-plant nitrate test; PSNT, pre-sidedress nitrate test).

Tools	Pros	Cons	Citations
Yield Goal	Mass balance approach that is easily calculated. Nitrogen recommendations can be adjusted to account for soil N using credits (previous crop and residual soil NO_3–N measurements).	Poor relationships observed between YG calculations and EONR due to the uncertainty of final yields, management, previous crop effects, soil N supply, corn and fertilizer prices, and fertilizer use efficiency. Additionally, this method does not account for within-field variability due to soil and water properties.	Stanford; 1973; Lory and Scharf, 2003; Sawyer et al., 2006
PPNT	Soil NO_3–N levels can be assessed for residual N and N supplied by manure that could be available for plant use. Can be used as an adjustment to other N recommendations. Sampling can be taken during a lull in seasonal work.	Not a useful tool in more humid regions due to N loss during wet springs. Inaccurate test results due to varying weather affecting N mineralization rates. Additional cost and labor required. Requires deep sampling, down to 0.60 m or deeper.	Magdoff et al., 1984; Bundy and Andraski, 1995; Schröder et al., 2000; Lory and Scharf, 2003; van Es et al., 2007
PSNT	Has potential for better accounting of N loss from leaching or denitrification and N inputs from mineralization than PPNT. Successful at identifying N-sufficient sites.	Additional in-season sampling required and limited by wet conditions and short laboratory turn around. Limited by N loss due to temperature and rainfall immediately before and after sampling. Does not account for within-field spatial variability that results from variable soil and water interactions.	Magdoff et al., 1984; Fox et al., 1989; Magdoff, 1991; Meisinger et al., 1992; Andraski and Bundy, 2002

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Table 1. (Continued).

Tools	Pros	Cons	Citations
MRTN	Nitrogen response trials are used to determine N rates. Data are easily updated with additional experimental N-rate trials. Calculations reflect current economic status by including the price of fertilizer and corn. Provides a range that is within $1.00 that farmers can use depending on their risk level.	Does not address the issue of the year to year temperature or rainfall variability. Cannot predict site-specific N requirements and unlikely to accurately estimate EONR for each specific environment. Does not account for within-field spatial variability due to soil and water properties. Must estimate what the price of corn will be at the end of the season.	Nafziger et al., 2004; Sawyer et al., 2006; van Es et al., 2007
Crop Growth Models	Estimates possible weather scenarios during a growing season to minimize N loss and predict N supplied by the soil. Non-static N recommendation based on the genetic, environmental, and management conditions.	Initial inputs require time and money. Models may need to be calibrated to specific climate and soil conditions. Many parameters are estimated or generalized.	van Es et al., 2007; Setiyono et al., 2011; Sawyer, 2013
Canopy Reflectance Sensing	Nitrogen recommendations can be adjusted for plant response to soil and water variability within fields. Provides a real-time assessment of corn N status during the season. Various algorithms allow for adaptability for different conditions. Works well with high soil variability or in scenarios of uncertain N.	Expensive upfront costs for sensors and applicators. Needs a high-N area to normalize reflectance values. The sensor is not sensitive to within field changes in crop height. Hard to "see" slight N deficiency. Confounded by other plant stresses (e.g., sulfur). The amount of crop canopy closure affects readings, excessive soil exposure resulting in a diluted index value and a closed canopy results in saturated measurements.	Shanahan et al., 2008; Holland and Schepers, 2010; Kitchen et al., 2010; Franzen, 2016

Table 2: Methods and implementation costs associated with corn N recommendation tools included this investigation. The implementation cost and required soil analysis are reported in parenthesis. Tool descriptions include YG as yield goal, PPNT as pre-plant nitrate test, and PSNT 0 and PSNT 45 as the pre-sidedress nitrate test with 0 and 45 kg N ha^{-1} applied at-planting, respectively. Variables used in calculations and implementation costs are Pop as plant population, OM as organic matter, and CEC as cation exchange capacity.

Tools	**Approach & Calculation**	**Reference**	**Implementation Costs**[§¶#]
General YG	Calculation using an expected yield and a soybean credit of 45 kg N ha^{-1}. $N_{rec} = 1.12^{\dagger} \times [1.2 \times YG - N_{credit}]$	Stanford,1973	Application Cost
IN YG	Calculation using an expected yield and a soybean credit of 34 kg N ha^{-1}. $N_{rec} = 1.12^{\dagger} \times [-27 + 1.36 \times YG - N_{credit}]$	Vitosh et al., 1996	Application Cost
MN YG	Calculation using an expected yield, organic matter content, and soybean credit of 22 to 45 kg N ha^{-1}. Soils are grouped into either low or high organic matter content with 30 g OM kg^{-1} soil being the threshold. *(Table 1 of publication)*	Schmitt et al., 2002	Application Cost
MO YG	Calculation using an expected yield, plant population, and N supplying power of the soil based on organic matter and cation exchange capacity, and a soybean credit of 34 kg N ha^{-1}. $N_{rec} = 1.12^{\dagger} \times [0.9 \times YG + 4 \times Pop - N_{OM\text{-}credit} - N_{credit}]$	Brown et al., 2004	Application Cost + Sampling Collection + Sample Analysis (\$2.00 ha^{-1}; OM & CEC)
NE YG	Calculation using an expected yield, measured or estimated inorganic soil NO_3–$N_{(0–1.20\ m)}$, measured or estimated N supplied from organic matter, and a soybean credit of 39 or 50 kg N ha^{-1}, for sandy and non-sandy soils, respectively. An estimated amount of N applied through irrigation is also credited. The N recommendation rate is adjusted for soil texture classification and time of N fertilizer application. $N_{rec} = 1.12^{\dagger} \times [35 + (1.2 \times YG) - (8 \times NO_3\text{–}N_{(0–1.20\ m)}) - 0.14 \times YG \times OM - N_{Credit}] \times Time_{adj} \times Price_{adj}$	Shapiro et al., 2008)	Application Cost + Sampling Collection + Sample Analysis (\$2.50 ha^{-1}; OM & NO_3–N)

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Table 2. (Continued).

Tools	Approach & Calculation	Reference	Implementation Costs[§¶#]
State-Specific YG	Sites within each state only used their respective state's YG method. The WI sites were excluded as no YG tool was used in WI. Yield goal tools not already listed are as follows: *IA YG = 1.12† × [1.22 × YG] or 1.12† × [0.9 × YG] for fine-silty Hapludolls – up to 56 kg N ha-1 soybean credit* IL YG used the General YG, and the ND YG used the ND PPNT.	Voss and Killorn, 1998; Hoeft and Peck, 1999.	Application Cost + Sampling Collection + Sample Analysis ($2.50 ha^{-1}; OM & NO_3–N)
General PPNT	The calculation is the measured soil NO_3–$N_{(0–0.60\ m)}$ concentration (converted to mass) subtracted from MRTN‡. $N_{rec} = 1.12^{\dagger} \times [MRTN^{\ddagger} – NO_3–N_{(0–0.60\ m)}]$	Bundy et al., 1999	Application Cost + Sampling Collection + Sample Analysis ($1.25 ha^{-1}; NO_3–N)
MN PPNT	The calculation is 60% of the measured soil NO_3–$N_{(0–0.60\ m)}$ concentration (converted to mass) subtracted from MRTN‡. $N_{rec} = 1.12^{\dagger} \times [MRTN^{\ddagger} – (0.60 \times NO_3–N_{(0–0.60\ m)})]$	Kaiser et al., 2016	Application Cost + Sampling Collection + Sample Analysis ($1.25 ha^{-1}; NO_3–N)
ND PPNT	The calculation is the measured soil NO_3–$N_{(0–0.60\ m)}$ concentration (converted to mass) subtracted from the ND YG calculation and using a soybean credit of 45 kg N ha^{-1}. $N_{rec} = 1.12^{\dagger} \times [1.2 \times YG – NO_3–N_{(0–0.60\ m)} – N_{credit}]$	Franzen, 2010	Application Cost + Sampling Collection + Sample Analysis ($1.25 ha^{-1}; NO_3–N)
WI PPNT	Calculation using the measured soil NO_3–N concentration (converted to mass) in the top 0.90 m (sample taken down to 0.60 m and last 0.30 m is estimated) subtracted from MRTN‡. To account for background soil NO_3–N 56 kg N ha^{-1} is subtracted from the total profile NO_3–N value. $N_{rec} = 1.12^{\dagger} \times [MRTN^{\ddagger} – (\Sigma NO_3–N_{(0–0.90\ m)} – 50)]$, *no adjustments made if the sum of* NO_3–N *is below 56 kg N ha*$^{-1}$.	Laboski and Peters, 2012	Application Cost + Sampling Collection + Sample Analysis ($1.25 ha^{-1}; NO_3–N)

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Table 2. (Continued).

Tools	Approach & Calculation	Reference	Implementation Costs[§¶#]
General PSNT	MRTN or YG recommendation is adjusted proportionally based on if soil NO_3–$N_{(0–0.30\ m)}$ concentration is below 25 mg kg^{-1} and above 10 mg kg^{-1}. The full recommended rate is applied if the soil NO_3–$N_{(0–0.30\ m)}$ concentration is below 10 mg kg^{-1} and no additional N is applied if it is above 25 mg kg^{-1}.	Fernández et al., 2009	Application Cost + Sampling Collection + Sample Analysis ($0.75 ha^{-1}; NO_3–N)
IA PSNT	Calculated using measured soil NO_3–$N_{(0–0.30\ m)}$ concentration and a critical limit of 25 mg kg^{-1}. To determine the N recommendation when NO_3–$N_{(0–0.30\ m)}$ is below the critical limit, the difference between the critical limit and the measured NO_3–$N_{(0–0.30\ m)}$ concentration is multiplied by 8. The critical limit is reduced by 3 to 5 mg kg^{-1} when spring precipitation is 20% above normal amounts. $N_{rec} = 1.12^{\dagger} \times [(25\ mg\ kg^{-1} - NO_3\text{–}N_{(0–0.30\ m)}\ mg\ kg^{-1}) \times 8]$	Blackmer et al., 1997	Application Cost + Sampling Collection + Sample Analysis ($0.75 ha^{-1}; NO_3–N)
IN PSNT	Calculation using yield goal and soil NO_3–$N_{(0–0.30\ m)}$ concentration (*Table 2 of publication*).	Brouder and Mengel, 2003	Application Cost + Sampling Collection + Sample Analysis ($0.75 ha^{-1}; NO_3–N)
WI PSNT	A soil N credit is calculated based on soil NO_3–$N_{(0–0.30\ m)}$ concentration and on the yield potential of the soil. No N application is recommended if the measured soil NO_3–$N_{(0–0.30\ m)}$ concentration is above 21 mg kg^{-1}. No N credits are applied if the soil NO_3–$N_{(0–0.30\ m)}$ concentration is below 10 mg kg^{-1}. (*Table 6.6 of publication*)	Laboski and Peters, 2012	Application Cost + Sampling Collection + Sample Analysis ($0.75 ha^{-1}; NO_3–N)
MRTN	Yield response of N response trials spanning multiple years. From each trial, the yield is modeled as a function of N fertilizer and the N recommendation is determined by adjusting the price of corn and N fertilizer. Multiple N recommendations are grouped by geographical locations or soil properties.	Sawyer et al., 2006	Application Cost

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Table 2. (Continued).

Tools	Approach & Calculation	Reference	Implementation Costs§¶#
Maize-N	Computer simulation of soil and crop processes to account for N uptake and removal from the root zone. Uses information based on soil, crop hybrid, management, economic inputs, and historical and daily weather.	Setiyono et al., 2011	Application Cost + Sampling Collection + Sample Analysis ($2.75 ha^{-1}; OM, NO_3–N, pH, & Bulk Density)
Canopy Reflectance Sensing	Nitrogen recommendations are based on reflectance wavelengths measured with proximal sensors.	Holland and Schepers, 2010	Custom Application Costs†† ($1.40 ha^{-1} more than split application cost)

†1.12 was used to convert N recommendations from lbs N ac^{-1} to kg N ha^{-1}.

‡ MRTN values were used except when states did not recommend MRTN, in which case that state's yield goal calculation was used.

§ Application costs: at-planting ($13.70 ha^{-1}) and split ($13.70 ha^{-1} + $28.40 ha^{-1}) applications estimated from Iowa Farm Custom Rate Survey using the average reported cost of applying dry bulk fertilizer (Plastina et al., 2017)

¶ Sample collection costs: $1.90 ha^{-1}, $2.80 ha^{-1}, and $3.80 ha^{-1} were used for shallow (0 – 0.30 m), medium (0 – 0.60 m), and deep (0 – 0.90 m) soil samples, respectively. Costs were based on the average reported wages ($15.25 h^{-1}) for operating machinery from the Iowa Farm Rate Survey (Plastina et al., 2017) and assuming a sampling rate of 8, 6, and 4 ha^{-1} for shallow, medium, and deep soil samples, respectively.

Sample analysis costs: The cost associated with analyzing samples was determined by taking the average of five soil-testing laboratories throughout the U.S. Midwest that were either land grant or commercially operated (Agvise Laboratories Inc., Midwest Labs Inc., North Dakota State University, University of Missouri, and University of Wisconsin-Madison). The cost increased with each additional depth analyzed.

†† The custom application cost was estimated using the reported average top-dress liquid fertilizer application rate ($28.40 ha^{-1}) from the Iowa Farm Rate Survey (Plastina et al., 2017). It was assumed that 50% of the top-dress application cost comes from machinery upkeep and acquisition and 50% from labor and fuel (R. Massey, personal communication, 2017). The cost of using canopy reflectance sensors was calculated as 10% ($1.40 ha^{-1}) of the base machinery upkeep and acquisition costs resulting in a total top-dress application cost of $29.90 ha^{-1}.

Table 3. Significant linear regression relationships between each N recommendation tool and the economic optimum nitrogen rate (EONR). Both at-planting and split N application tools are reported. Tool descriptions include YG as yield goal, PPNT as pre-plant nitrate test, and PSNT 0 and PSNT 45 as the pre-sidedress nitrate test with 0 and 45 kg N ha^{-1} applied at-planting, respectively. Bolded tool names indicate a significant and positive relationship between recommendations and EONR were found ($\alpha = 0.10$). If blank, then non-significant. Dashes indicate not applicable.

		At-Planting				**Split**			
N Recommendation Tool	**n**	***P*-Value**	**r^2**	**Intercept**	**Slope**	***P*-Value**	**r^2**	**Intercept**	**Slope**
Farmer NR	49	0.51				0.89			
General YG	49	0.01	0.13	339	–0.74	0.01	0.13	311	–0.65
IN YG	49	0.02	0.10	316	–0.60	0.02	0.10	291	–0.53
MN YG	49	0.11				0.06	0.07	298	–0.82
MO YG	49	0.02	0.10	329	–0.68	0.02	0.11	306	–0.61
NE YG	49	0.47				0.67			
State-Specific YG†	43	0.17				**0.04**	**0.10**	**74**	**0.51**
General PPNT	**47**	**<0.01**	**0.15**	**63**	**0.83**	-	-	-	-
MN PPNT	**47**	**0.01**	**0.13**	**49**	**0.84**	-	-	-	-
ND PPNT	47	0.70				-	-	-	-
WI PPNT	**44**	**<0.01**	**0.16**	**50**	**0.72**	-	-	-	-
MRTN	36	0.53				0.45			
Maize-N	49	0.50				0.96			
General PSNT 0	49	-	-	-	-	**0.01**	**0.13**	**76**	**0.55**
IA PSNT 0	49	-	-	-	-	**<0.001**	**0.24**	**54**	**0.79**
IN PSNT 0	49	-	-	-	-	0.21			
WI PSNT 0	49	-	-	-	-	**0.02**	**0.11**	**90**	**0.46**
General PSNT 45	49	-	-	-	-	**0.07**	**0.07**	**126**	**0.31**

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Table 3. (Continued).

N Recommendation Tool	n	At-Planting				Split			
		P-Value	r^2	Intercept	Slope	*P*-Value	r^2	Intercept	Slope
IA PSNT 45	49	-	-	-	-	**<0.01**	**0.14**	**99**	**0.49**
IN PSNT 45	49	-	-	-	-	**0.01**	**0.12**	**91**	**0.43**
WI PSNT 45	49	-	-	-	-	0.13			
Canopy Reflectance Sensing	49	-	-	-	-	**0.01**	**0.13**	**93**	**0.62**

† Indicates that each state used their respective state yield goal recommendation

Table 4. The precision and accuracy of each N recommendation tool were evaluated using the average difference (N recommendation tool – EONR), RMSE of the difference between a tools' N recommendation and EONR, and the percentage of sites ±30 kg N ha^{-1} of EONR or "relatively close to EONR" (RC-EONR). Tools were evaluated across 49 sites from 2014 to 2016. The percentage of sites (n) included in the evaluation differed for each tool based on the availability of information to test the tool. Tools include yield goal (YG), pre-plant nitrate test (PPNT), pre-sidedress nitrate test (PSNT) with 0 and 45 kg N ha^{-1} applied at-planting, MRTN, Maize-N crop growth model, and canopy reflectance sensing using the Holland and Schepers algorithm. Tools with a significant relationship with EONR (Table 3) are bolded. Dashes indicate not applicable.

		At-Planting			Split		
N Recommendation Tool	**n**	**Average**	**RMSE**	**RC-EONR**	**Average**	**RMSE**	**RC-EONR**
		----- kg N ha^{-1} ----		%	----- kg N ha^{-1} ----		%
Farmer NR	49	24	88	31	31	84	29
General YG	49	58	117	14	65	113	18
IN YG	49	73	127	14	80	125	14
MN YG	49	–6	90	24	2	81	41
MO YG	49	65	120	16	72	117	20
NE YG	49	–12	86	35	–27	81	37
State-Specific YG†	43	20	83	23	**22**	**72**	**37**
General PPNT	**47**	**–40**	**85**	**21**	-	-	-
MN PPNT	**47**	**–26**	**80**	**32**	-	-	-
ND PPNT	47	7	93	13	-	-	-
WI PPNT	**44**	**–5**	**71**	**34**	-	-	-
MRTN	36	16	77	39	19	72	42
Maize-N	49	–44	116	18	–31	112	24
General PSNT 0	**49**	-	-	-	**–4**	**70**	**43**
IA PSNT 0	**49**	-	-	-	**–25**	**68**	**41**
IN PSNT 0	49	-	-	-	40	83	24
WI PSNT 0	**49**	-	-	-	**–5**	**73**	**41**
General PSNT 45	**49**	-	-	-	**–44**	**92**	**29**
IA PSNT 45	**49**	-	-	-	**–33**	**79**	**47**
IN PSNT 45	**49**	-	-	-	**2**	**75**	**41**
WI PSNT 45	49	-	-	-	–38	90	35
Canopy Reflectance Sensing	**49**	-	-	-	**–49**	**85**	**22**

† Indicates that each state used their respective state yield goal recommendation

Table 5. The best-fit models (Linear, Quadratic, Plateau-Linear, Plateau-Quadratic, and Exponential) for explaining N lost from the soil profile (0-0.90 m) in-season and post-harvest (residual soil nitrate) for each site and N application timings. The goodness of fit (r2/R2) values of each model are also reported for each significant (α = 0.05) model (NS = non-significant).

			At-Planting				**Split**			
			Inseason N loss		**Residual Soil Nitrate**		**Inseason N loss**		**Residual Soil Nitrate**	
Year	**State**	**Site**	**Model**	**R^2**	**Model**	**R^2**	**Model**	**R^2**	**Model**	**R^2**
2014	IA	Ames	Exponential	0.33	Plateau-Linear	0.56	NS		Plateau-Linear	0.50
	IA	MasonCity	NS		Plateau-Quadratic	0.87	Quadratic	0.77	Exponential	0.92
	IL	Brownstown	Linear	0.88	Plateau-Quadratic	0.50	Exponential	0.54	Plateau-Linear	0.41
	IL	Urbana	Plateau-Quadratic	0.30	Plateau-Linear	0.27	Plateau-Linear	0.27	Plateau-Linear	0.38
	IN	Loam	Plateau-Linear	0.93	Plateau-Quadratic	0.48	Linear	0.34	Plateau-Quadratic	0.76
	IN	Sand	Linear	0.16	Plateau-Quadratic	0.50	NS		Exponential	0.67
	MN	NewRichland	Linear	0.66	Linear	0.33	Linear	0.25	Plateau-Linear	0.62
	MN	StCharles	Linear	0.29	Plateau-Linear	0.57	NS		Plateau-Linear	0.62
	MO	Bay	NS		Plateau-Quadratic	0.80	NS		Plateau-Quadratic	0.66
	MO	Troth	NS		Plateau-Quadratic	0.79	NS		Exponential	0.79
	ND	Amenia	NS		Plateau-Linear	0.46	NS		Plateau-Quadratic	0.50
	ND	Durbin	Plateau-Quadratic	0.72	Plateau-Quadratic	0.35	NS		Plateau-Linear	0.62
	NE	Brandes	Linear	0.63	NS		Plateau-Quadratic	0.63	NS	
	NE	SCAL	Linear	0.47	Plateau-Linear	0.72	Linear	0.46	Plateau-Quadratic	0.91
	WI	Steuben	NS		Plateau-Quadratic	0.85	Plateau-Linear	0.42	Plateau-Quadratic	0.91

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Table 5. (Continued).

			At-Planting				Split			
			Inseason N loss		Residual Soil Nitrate		Inseason N loss		Residual Soil Nitrate	
Year	**State**	**Site**	**Model**	**R^2**	**Model**	**R^2**	**Model**	**R^2**	**Model**	**R^2**
	WI	Wauzeka	Linear	0.48	Plateau-Linear	0.66	Quadratic	0.53	Linear	0.54
2015	IA	Boone	Quadratic	0.65	Plateau-Linear	0.73	Linear	0.16	Plateau-Linear	0.60
	IA	Lewis	NS		Plateau-Linear	0.68	NS		Linear	0.49
	IL	Brownstown	Linear	0.82	NS		Linear	0.79	Plateau-Linear	0.19
	IL	Urbana	Linear	0.58	Plateau-Quadratic	0.63	Linear	0.25	Plateau-Quadratic	0.51
	IN	Loam	Quadratic	0.67	Plateau-Quadratic	0.90	Plateau-Linear	0.36	Exponential	0.90
	IN	Sand	NS		Plateau-Linear	0.55	Plateau-Quadratic	0.53	Plateau-Quadratic	0.82
	MN	NewRichland	Plateau-Linear	0.16	Plateau-Quadratic	0.72	NS		Plateau-Linear	0.83
	MN	StCharles	NS		Plateau-Linear	0.75	NS		Plateau-Linear	0.60
	MO	LoneTree	Linear	0.79	NS		Linear	0.56	NS	
	MO	Troth	Linear	0.69	Linear	0.15	Linear	0.81	NS	
	ND	Amenia	NS		Exponential	0.59	Linear	0.14	Exponential	0.52
	ND	Durbin	NS		Exponential	0.65	NS		Linear	0.44
	NE	Brandes	Linear	0.95	Linear	0.32	Plateau-Quadratic	0.89	Linear	0.40
	NE	SCAL	Linear	0.71	Plateau-Quadratic	0.78	NS		Quadratic	0.74
	WI	Belmont	NS		Linear	0.66	NS		Exponential	0.68
	WI	Darlington	Linear	0.33	Plateau-Linear	0.69	NS		Quadratic	0.80

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Table 5. (Continued).

			At-Planting				Split			
			Inseason N loss		Residual Soil Nitrate		Inseason N loss		Residual Soil Nitrate	
Year	**State**	**Site**	**Model**	**R^2**	**Model**	**R^2**	**Model**	**R^2**	**Model**	**R^2**
2016	IA	Crawford	Plateau-Linear	0.40	Plateau-Quadratic	0.34	Plateau-Quadratic	0.76	Plateau-Quadratic	0.85
	IA	Story	Plateau-Linear	0.32	Exponential	0.79	Linear	0.37	Plateau-Linear	0.73
	IL	Shumway	Plateau-Quadratic	0.50	Plateau-Linear	0.69	Quadratic	0.30	Plateau-Linear	0.94
	IL	Urbana	NS		Plateau-Quadratic	0.74	Linear	0.28	Plateau-Linear	0.82
	IN	Loam	NS		Plateau-Quadratic	0.82	NA		Plateau-Linear	0.47
	IN	Sand	NS		Plateau-Linear	0.51	Plateau-Linear	0.31	Plateau-Linear	0.57
	MN	Becker	Plateau-Linear	0.83	NS		Linear	0.69	Plateau-Quadratic	0.27
	MN	Waseca	Plateau-Linear	0.75	Plateau-Linear	0.25	Quadratic	0.76	Plateau-Linear	0.53
	MO	Bradford	Plateau-Quadratic	0.49	Quadratic	0.54	NS		Quadratic	0.67
	MO	Loess	NS		Plateau-Quadratic	0.64	NS		Plateau-Quadratic	0.79
	MO	Troth	NS		Quadratic	0.47	Linear	0.19	Plateau-Quadratic	0.51
	ND	Amenia	NS		Linear	0.53	Plateau-Quadratic	0.36	Quadratic	0.50
	ND	Durbin	Plateau-Quadratic	0.49	NS		NS		Linear	0.58
	NE	Kyes	Exponential	0.59	Plateau-Linear	0.33	NS		Plateau-Quadratic	0.47
	NE	SCAL	Plateau-Linear	0.91	Plateau-Quadratic	0.66	Linear	0.47	Exponential	0.78
	WI	Lorenzo	Linear	0.25	NS		Plateau-Quadratic	0.34	NS	
	WI	Plano	NS		Plateau-Quadratic	0.72	NS		Plateau-Linear	0.78

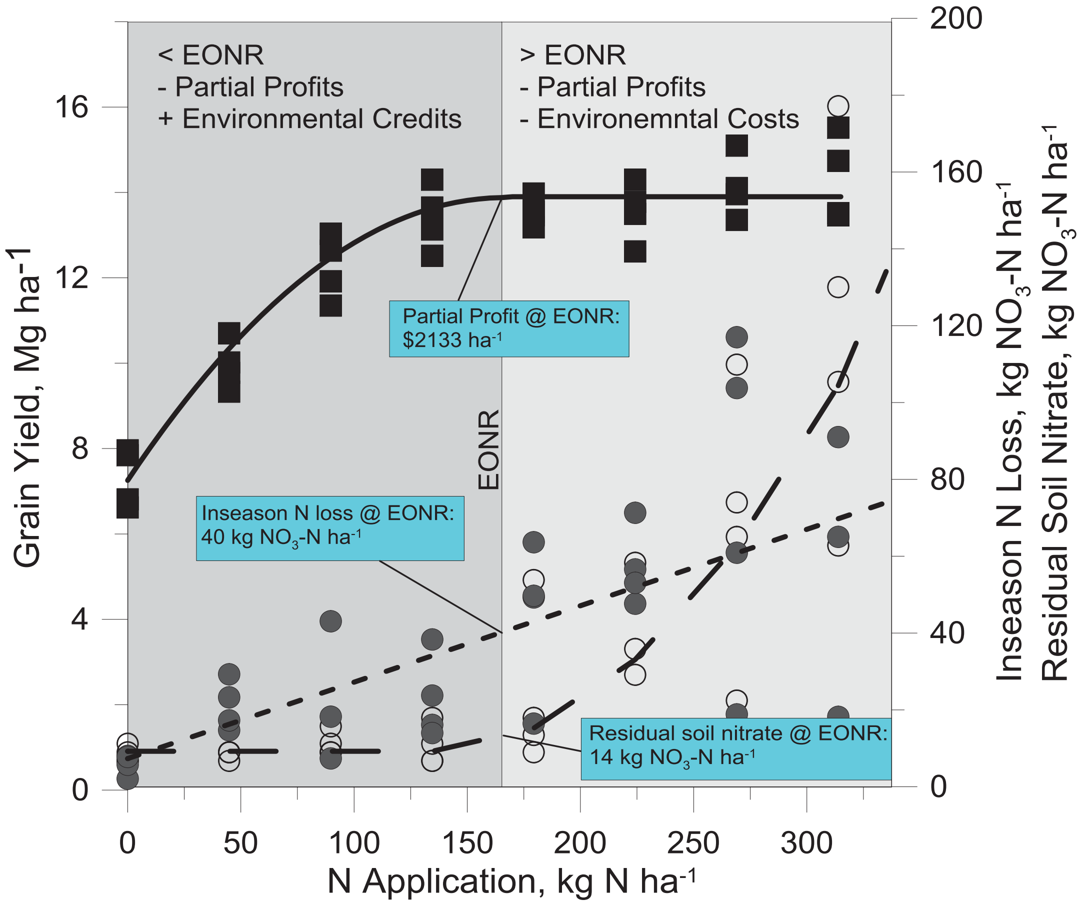

Fig. 1. An example of one site's partial profit and environmental cost is shown using grain yield, inseason N loss, and post-harvest residual soil nitrate. For EONR, grain yield in response to applied N is shown as a quadratic-plateau model (squares and solid line). The calculated inseason N loss (closed circles and small dash line) and residual soil nitrate (open circles and large dash line) as a response to applied N (specific models used are reported in Table 5). The partial profit for EONR was calculated using the interpolated grain yield from the best-fit line (13.5 Mg ha^{-1} × $158 Mg^{-1}). An environmental costs for EONR was calculated by multiplying the sum of the interpolated inseason N loss and residual soil nitrate multiplying by a prevention cost [(40 + 14 kg NO_3–N ha^{-1}) × $2.75 kg^{-1} NO_3–N = $148.5 ha^{-1}). A total combined cost for EONR was calculated by adding the partial profit and environmental cost together. The partial profit, environmental cost, and total combined cost were calculated for each N recommendation tool. Additional implementation costs associated with utilizing the tools were subtracted from the partial profit (Table 2). Each assessment was made relative to EONR. Tools that underestimated EONR (dark gray area) resulted in decreased partial profits but provided an environmental credit. Tools that overestimated EONR (light gray area) resulted in a decrease to partial profits and environmental costs.

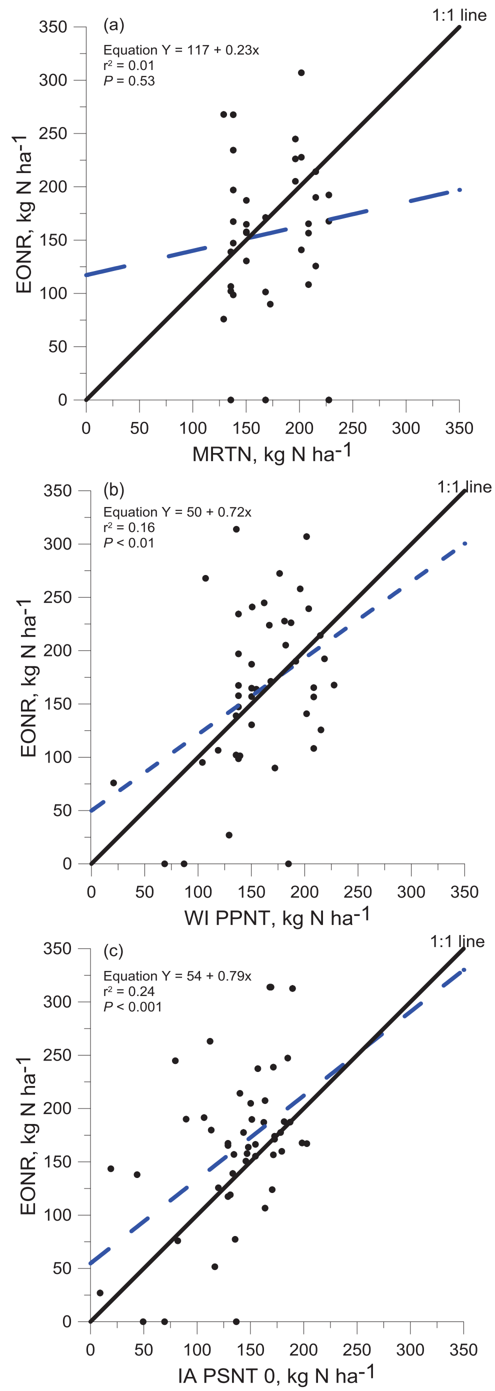

Fig. 2. Measured economical optimal nitrogen rate (EONR) related to a) MRTN, b) the WI pre-plant soil nitrate test (PPNT), and c) the IA pre-sidedress soil nitrate test (PSNT) with 0 kg N ha^{-1} applied at-planting. The 1:1 indicates a perfect prediction of EONR. The dashed is the best-fit linear regression line.

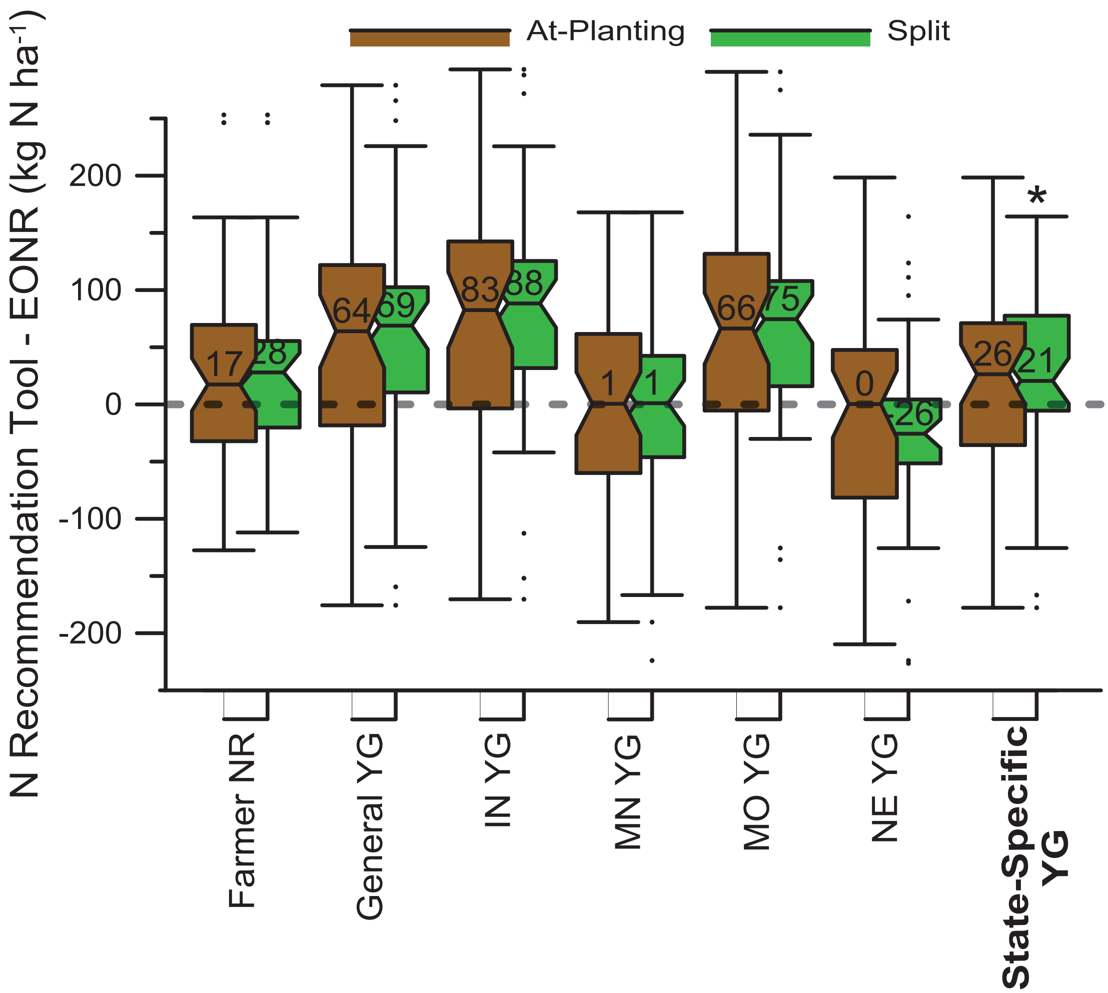

Fig. 3. Box and whisker plots showing the difference between each yield goal (YG) based N recommendation and the economically optimal N rate (EONR) for both at planting and split N application timings. The median is reported by the value in the middle of the box. Notches on the side of each box indicate the 95% confidence interval around the median. Limits of the box indicate the first and third quartile, whiskers indicate 1.5 × IQR, and small circles indicate outliers. Tools with a significant relationship with EONR (Table 3) are bolded and marked with a "*".

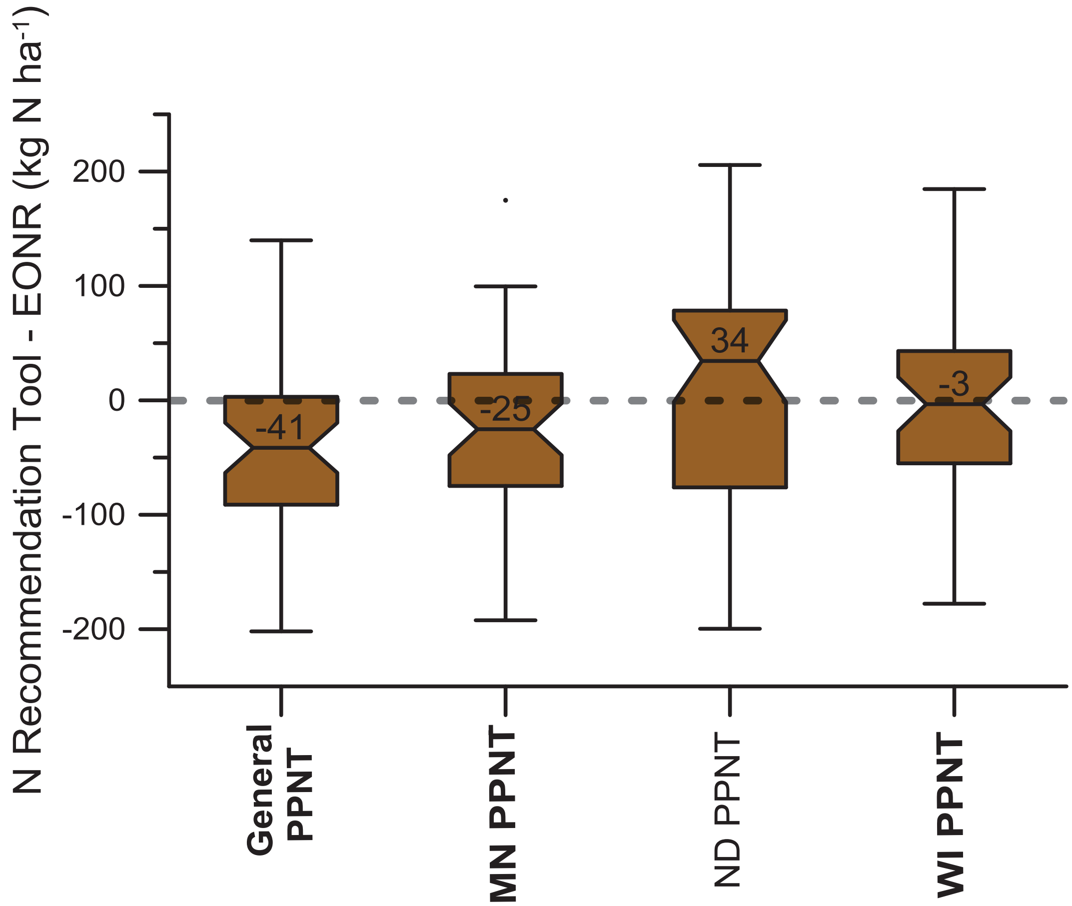

Fig. 4. Box and whisker plots showing the difference between each pre-plant soil nitrate test (PPNT) and the economically optimal N Rate (EONR). The median is reported by the value in the middle of the box. Notches on the side of each box indicate the 95% confidence interval around the median. Limits of the box indicate the first and third quartile, whiskers indicate 1.5 × IQR, and small circles indicate outliers. Tools with a significant relationship with EONR (Table 3) are bolded.

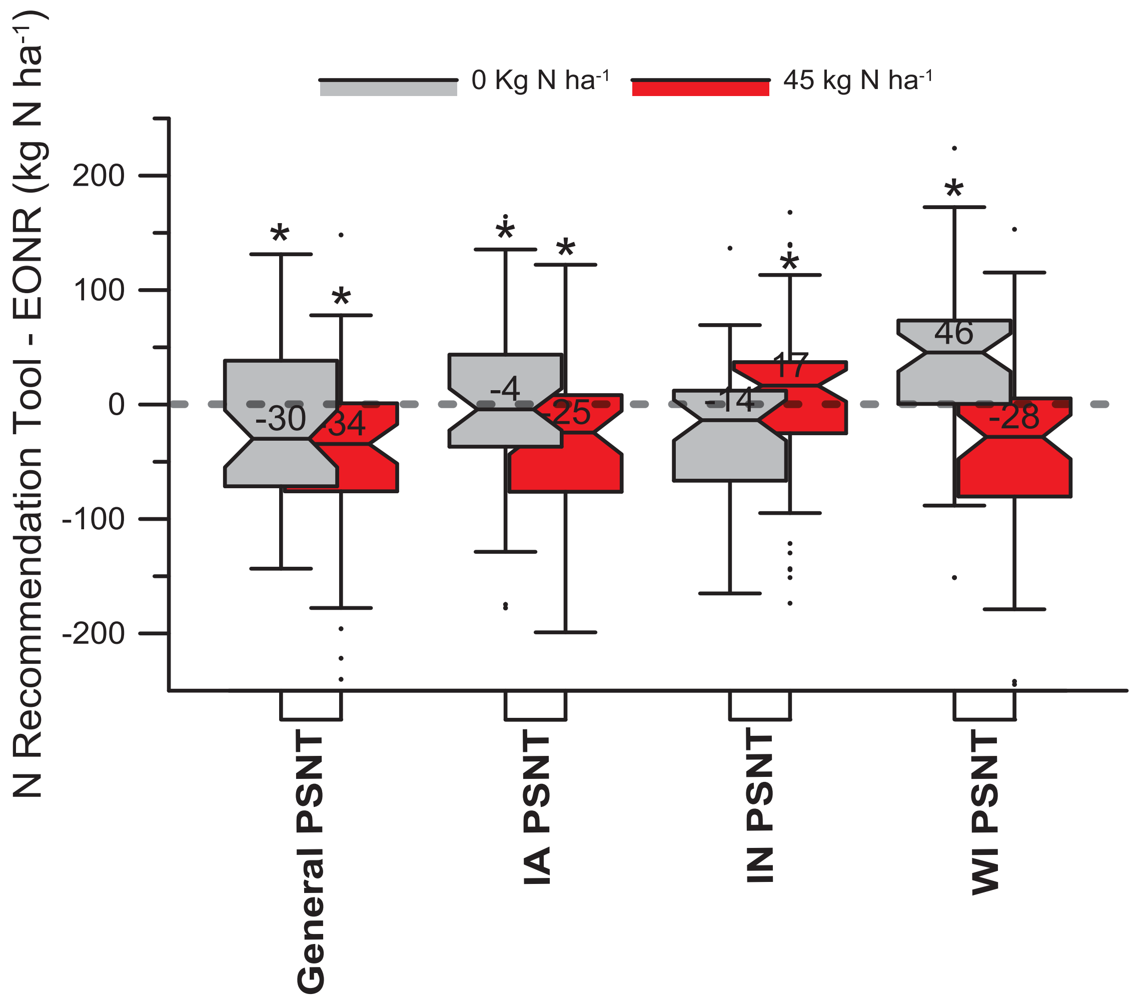

Fig. 5. Box and whisker plots showing the difference between each pre-sidedress soil nitrate test (PSNT) N recommendation and the economically optimal N rate (EONR). The PSNT tools evaluated for both 0 and 45 kg N ha^{-1} applied at-planting. The median is reported by the value in the middle of the box. Notches on the side of each box indicate the 95% confidence interval around the median. Limits of the box indicate the first and third quartile, whiskers indicate 1.5 × IQR, and small circles indicate outliers. Tools with a significant relationship with EONR (Table 3) are bolded and marked with a "*."

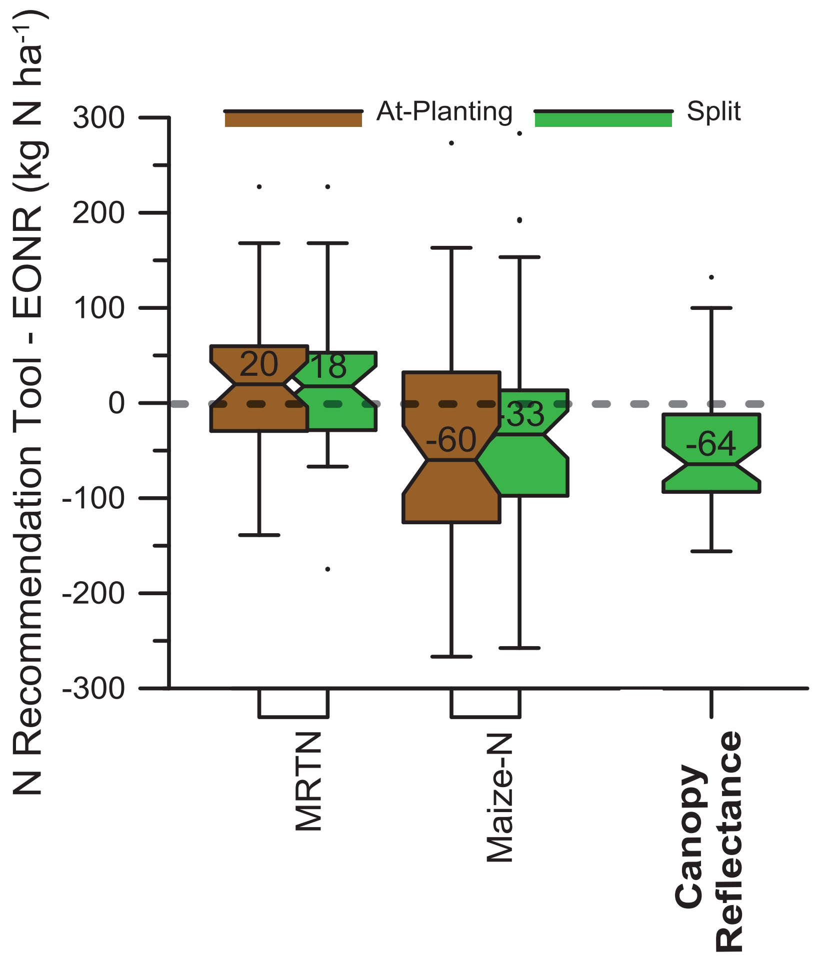

Fig. 6. Box and whisker plots showing the difference between each of the tools' N recommendation and the economically optimal N rate (EONR) for both at-planting and split N application timings. The median is reported by the value in the middle of the box. Notches on the side of each the box indicate the 95% confidence interval around the median. Limits of the box indicate the first and third quartile, whiskers indicate 1.5 × IQR, and small circles indicate outliers. Tools with a significant relationship with EONR (Table 3) are bolded.

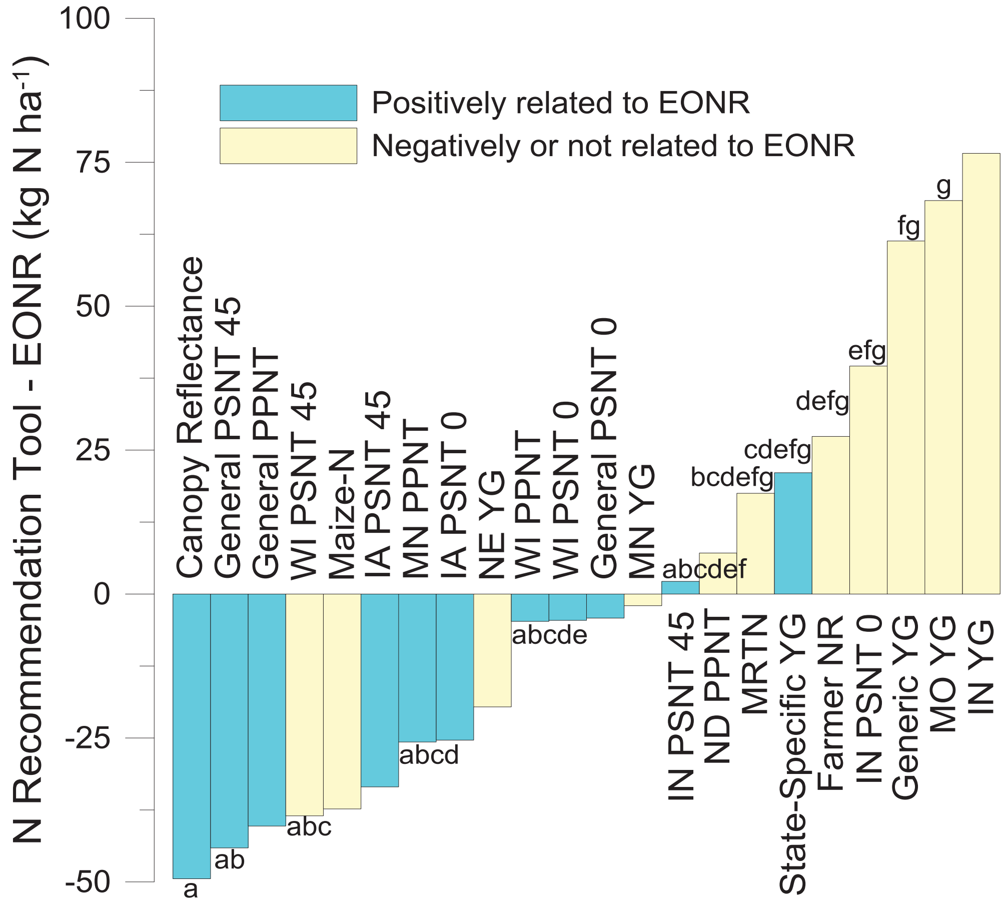

Fig. 7. Graph shows the mean difference between each N recommendation tool and the economically optimal N rate (EONR). Both at-planting and split N application tools are shown, but only tools with a significant relationship with EONR (Table 3) are highlighted in blue. Tool descriptions include YG as yield goal, PPNT as pre-plant nitrate test, and PSNT 0 and PSNT 45 as the pre-sidedress nitrate test with 0 and 45 kg N ha^{-1} applied at-planting, respectively. Significance mean separation was determined using Tukey honest significant difference test. Values not significant from each other ($\alpha > 0.05$) share similar lower case values. Tools not marked with letters share the same letter significance as tools to the left of them.

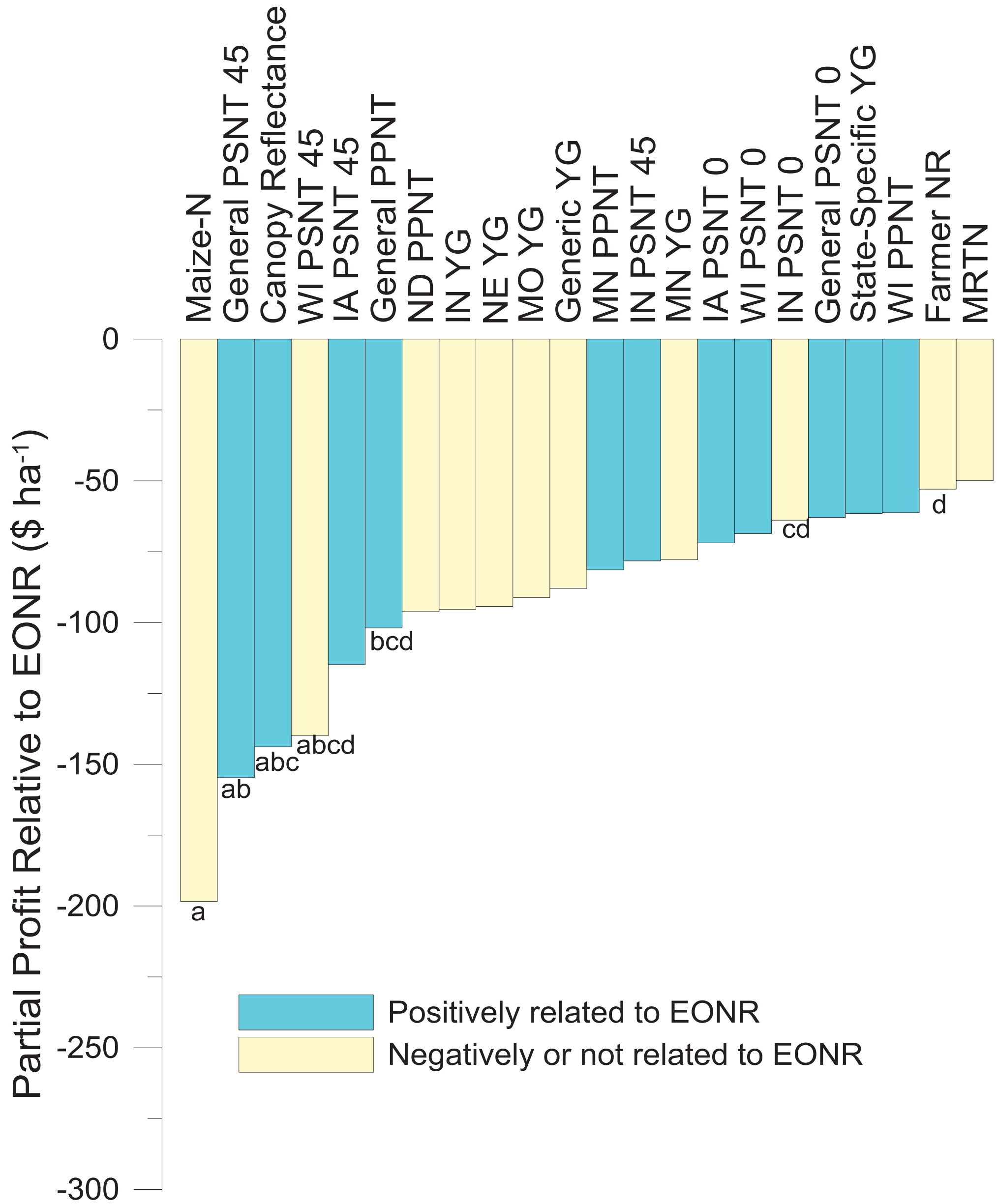

Fig. 8. Mean partial profit for N recommendation tools relative to the economically optimal N rate (EONR). Both at-planting and split N application tools are shown, but only tools with a significant relationship with EONR (Table 3) are highlighted in blue. Tool descriptions include YG as yield goal, PPNT as pre-plant nitrate test, and PSNT 0 and PSNT 45 as the pre-sidedress nitrate test with 0 and 45 kg N ha^{-1} applied at-planting, respectively. Significance mean separation was determined using Tukey honest significant difference test. Values not significant from each other ($\alpha > 0.05$) share similar lower case values. Tools not marked with letters share the same letter significance as tools to the left of them.

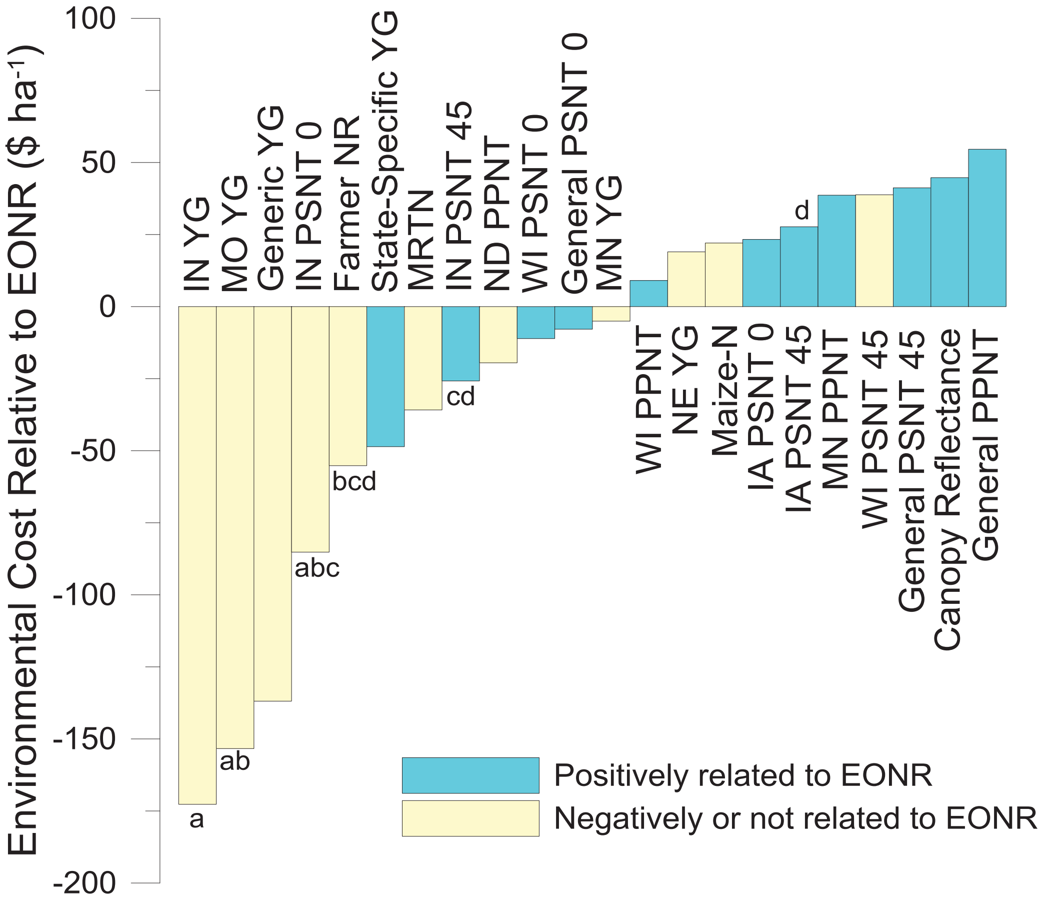

Fig. 9. Mean environmental cost for N recommendation tools relative to the economically optimal N rate (EONR). Both at-planting and split N application tools are shown, but only tools with a significant relationship with EONR (Table 3) are highlighted in blue. Tool descriptions include YG as yield goal, PPNT as pre-plant nitrate test, and PSNT 0 and PSNT 45 as the pre-sidedress nitrate test with 0 and 45 kg N ha^{-1} applied at-planting, respectively. Significance mean separation was determined using Tukey honest significant difference test. Values not significant from each other ($\alpha > 0.05$) share a similar lower case values. Tools not marked with letters share the same letter significance as tools to the left of them.

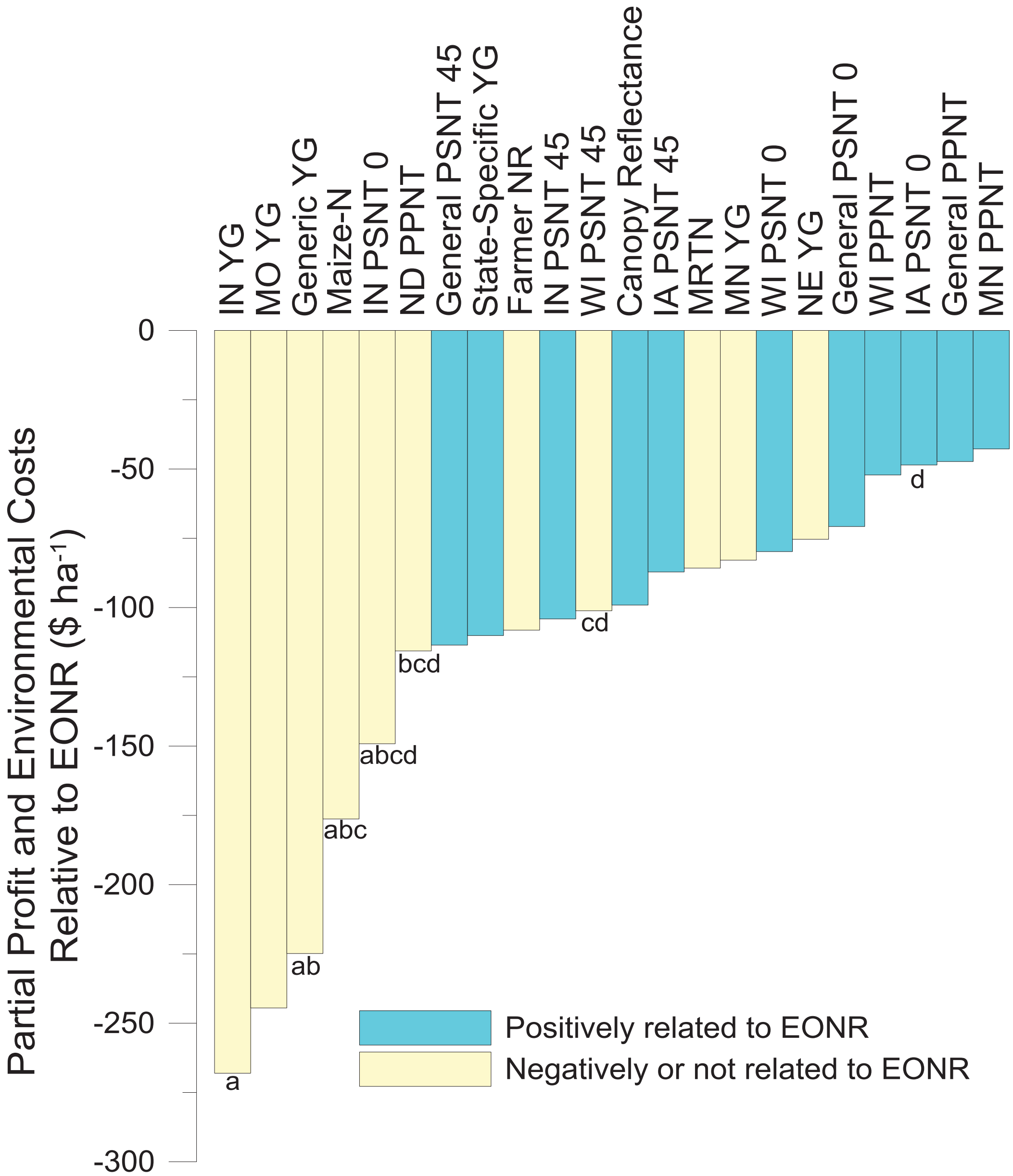

Fig. 10. Combined partial profit and environmental cost for N recommendation tools used relative to the economically optimal N rate (EONR). Both at-planting and split N application tools are shown, but only tools with a significant relationship with EONR (Table 3) are highlighted in blue. Tool descriptions include YG as yield goal, PPNT as pre-plant nitrate test, and PSNT 0 and PSNT 45 as the pre-sidedress nitrate test with 0 and 45 kg N ha^{-1} applied at-planting, respectively. Significance mean separation was determined using Tukey honest significant difference test. Values not significant from each other ($\alpha > 0.05$) share a similar lower case values. Tools not marked with letters share the same letter significance as tools to the left of them.

Chapter 3: A Comparison of Eight Statistical Algorithms for Improving Corn Nitrogen Recommendation Tools with Soil and Weather Information

ABSTRACT

Corn (*Zea mays* L.) nitrogen (N) fertilizer recommendation tools could better predict the economically optimal N rate (EONR) by incorporating soil and weather information. The objectives of this research were to 1) identify the best statistical algorithm that results in a parsimonious model for best-incorporating soil and weather information into N recommendation tools to improve predictions of EONR, and 2) evaluate the performance of the statistical algorithms with and without multicollinearity and two-way interactions. Eight algorithms [stepwise, ridge regression, least absolute shrinkage and selection operator (Lasso), elastic net regression, principal component analysis (PCA), partial least squares regression (PLS), Bayesian Lasso, and random forest] were evaluated using a dataset containing measured soil and weather variables from a regional database. Multiple algorithm modeling scenarios were examined with and without multicollinearity and with and without two-way interaction terms to identify the soil and weather variables that potentially could improve three N recommendation tools: 1) Farmer's N rate (NR), 2) Indiana yield goal (IN YG), and 3) canopy reflectance sensing. The out-of-sample error for the stepwise regression was an order of magnitude higher than all other models. The random forest model best adjusted each of the N recommendation tools regardless of modeling scenario (change in $r^2 \geq 0.72$ and change in RMSE ≥ 42 kg N ha^{-1}) but utilized all variables in the model. The lasso and elastic net had the least amount of variables in the final model regardless of modeling scenario and

had similar improvement when adjusting N recommendation tools for all but one modeling scenario. When adjusting the Farmer NR without multicollinearity or two-way interaction terms, the elastic net ($r^2 = 0.24$; $P < 0.001$; RMSE = 71 kg N ha^{-1}) improved the performance of the Farmer's NR compared to the lasso ($r^2 = 0.03$; $P = 0.25$; RMSE = 82 kg N ha^{-1}). From an agronomic standpoint, the elastic net would be a better method than the random forest for incorporating soil and weather information, as it performs well at selecting a minimum number of variables and is much easier to interpret than other algorithms.

INTRODUCTION

One approach used to maximize profits and minimize environmental issues associated with nitrogen (N) management in corn is to apply N fertilizer at rates close to the economically optimal N rate (EONR; Hong et al., 2007; Kyveryga et al., 2009; Bandura, 2017). However, EONR is unknown at the time of N application as it is calculated following grain harvest. Moreover, EONR varies considerably within a field and from year-to-year making EONR challenging to estimate (Scharf et al., 2005; Shanahan et al., 2008; Kyveryga et al., 2009). Both the spatial and temporal variability of EONR are driven by environmental, genetic, and management factors. More specifically, rainfall distribution, soil texture, soil water-holding capacity, plant genetics, management practices, and grain and fertilizer prices have all been shown to influence EONR (Dinnes et al., 2002; Kay et al., 2006; Schmidt et al., 2009; Zhu et al., 2009; Tremblay et al., 2012; Morris et al., 2018). Efforts have been made to incorporate many of these factors into N recommendation tools. Crop growth models for example, directly integrate weather, soil, and management factors through mass balance calculations to produce an N recommendation (Setiyono et al., 2011; Moebius-Clune et al., 2013). Nitrogen recommendations developed using this method vary in accuracy depending on the model, accuracy of input data, and location in which they are used (Setiyono et al., 2011; Moebius-Clune et al., 2013; Thompson et al., 2015; Jin et al., 2017).

Other N recommendation tools have incorporated some of the spatial and temporal factors affecting EONR to improve their performance. However, apart from the crop growth models, no one method has been able to incorporate as many of the factors known to affect EONR. For example, the yield goal method for generating a corn N rate traditionally is adjusted based on a previous soybean crop (Stanford, 1973). Other yield goal based methods have also included an estimate of N mineralized by organic matter or a measure of soil nitrate prior to N fertilizer application (Brown et al., 2004; Shapiro et al., 2008). The pre-sidedress nitrate test indirectly measures in-season mineralization rates and adjusts the sufficient N threshold based on spring precipitation (Blackmer et al., 1997). The MRTN incorporates multiple yield response studies grouped based on geographical boundaries, soil texture, and climatic conditions to better account for spatial and temporal variability (Sawyer et al., 2006b). Finally, canopy reflectance sensing assesses the color and biomass of corn plants at a very short spatial scale in order to integrate the plant and soil N status into an N recommendation (Kitchen et al., 2010). Even though these tools indirectly or directly incorporate soil and weather into their N recommendation process, these tools have been found to be poorly related with EONR (chapter 2), and therefore are not reliable for making N fertilizer recommendations over the US Corn Belt.

Incorporating additional factors into the N recommendation tools, known to affect EONR, could improve them. The incorporation of various weather and soil variables interactions improved the relationship of a canopy reflectance sensing algorithm's N recommendation to EONR from an r^2 of 0.14 to 0.43 (Bean et al., 2018). Others showed that including soil-specific information with a pre-plant soil test significantly improved the predictability of optimal N rate (r^2 = 0.92; Vanotti and Bundy, 1999). Furthermore, management zones delineated by soil parameters improved the profitability of using canopy reflectance sensing as an N recommendation tool (Roberts et al., 2012).

Statistical Algorithms

Stepwise Regression

From a statistical standpoint determining which soil and weather variables to incorporate into an N recommendation tool can be computationally inefficient depending on the algorithm that is used. A standard method used in agricultural research is regression and least squares to estimate parameter coefficients. Stepwise regression is an example of this method. The utility of stepwise regression is its ability to add or remove variables from a model in controlled steps to better determine which explanatory variables best relate to a response variable (Yamashita et al., 2007). However, stepwise regression has often been found to overestimate values as it puts a high bias on each of the parameters and relies heavily on the assumption of having a single best model (Whittingham et al., 2006; Zou, 2006). To account for the high bias of stepwise procedures, a penalty on parameters can be employed using either ridge regression or the Lasso algorithms (Tibshirani, 1996; Zhao and Yu, 2006; McDonald, 2009).

Penalization Regression Algorithms

The ridge regression works as a continual shrinkage method in which the residual sum of squares is minimized as each parameter's coefficient is adjusted close to zero, thus reducing the importance or influence of any one parameter (Hoerl and Kennard, 1970). In contrast, the Lasso regression reduces coefficients parameters to zero thus selecting essential variables and shrinking the number of model parameters simultaneously (Tibshirani, 1996). It is particularly useful with large datasets as it works efficiently and quickly (Friedman et al., 2010). The Lasso fails in the variable selection process, however, when the number of observations is less than the number of parameters in the model or when there are many highly correlated variables (Zou and Hastie, 2005). To account for this weakness, the elastic net algorithm has been suggested as a way to determine the best combination of both the ridge regression and Lasso (Zou and Hastie, 2005).

Principal Component Analysis and Partial Least Squares Regression

Apart from these penalization methods, other algorithms account for the weakness associated with regression analysis. The principal component analysis can overcome issues related to multicollinearity by transforming groups of explanatory variables into new variables or principal components. Principle components are determined by fitting a line through the explanatory variables that best captures the quantity and direction of the variance. The numbers of principal components that are determined are based on the number of explanatory variables. However, only the principal components that explain the most amount of variance are retained, resulting in a reduction of the number of new explanatory variables. These new variables are then regressed against the response variable. However, there is no guarantee that the newly devised principle component variables will explain the response variable (Jagadamma et al., 2008; Abdi and Williams, 2010). A similar technique to the principal component analysis is the partial least square regression. It works by finding the best relationship between the explanatory and response variables that explains the basic structure of the data. This is done using linear regression models to fit pairs of explanatory and response variables. The best prediction functions are then regressed against the explanatory variable (Geladi and Kowalski, 1986). Both the principal component analysis and partial least squares regression methods work well when the number of observations is less than the number of explanatory variables in the model.

Bayesian Lasso and Random Forest

There is a multitude of other algorithms that could also be helpful at incorporating soil and weather information into an N recommendation tool. Bayesian statistics are promising as prior knowledge or parameters can be incorporated into the analysis as an assigned prior distribution. These distributions are updated with collected data and conclusions are reported as probabilities (Theobald and Talbot, 2002; Kyveryga et al., 2013). The Bayesian Lasso has been found to act similarly to the Lasso but provides a better interval estimate for all parameters and is more computationally competitive (Park and Casella, 2008). Other machine learning processes that have the potential to identify and incorporate soil and weather data into N recommendation tools are decisions tree-based algorithms. Decisions trees create a model of decisions (like a flow chart) to predict a response variable. A model is created as data are continually split based on the explanatory variables until additional splits stop adding value to the prediction (Quinlan, 1986). Another commonly used method in machine learning is to ensemble multiple methods to provide a more accurate prediction. Random forest is an example of this approach. Random forest creates hundreds of decision trees, which are developed using a random subset of explanatory variables to define each split best. A final prediction is made by averaging all the trees predictions (Breiman, 1999; Grömping, 2009).

Improving Nitrogen Recommendation Tools

These statistical methods could be used to determine which soil and weather variables could be integrated into N recommendation tools to improve their predictability of EONR. However, identifying which soil and weather variables are necessary for adjusting each N recommendation tool can be computationally complex. To learn how best to improve N recommendation tools, eight different statistical methods were evaluated for utilizing data that contained more variables than observations and consisted of many highly correlated variables. The primary objective was to identify the best statistical algorithm that resulted in a parsimonious model and best-incorporated soil and weather information into an N recommendation tool. A secondary objective was to determine how these algorithms performed with and without multicollinearity and two-way interaction terms.

MATERIALS AND METHODS

This research was part of a public-private collaboration between DuPont Pioneer and eight U.S. Midwest universities (University of Iowa, University of Illinois Urbana-Champaign, University of Minnesota, University of Missouri, North Dakota State University, Purdue University, University of Nebraska-Lincoln, and University of Wisconsin-Madison). The data used in this project were developed from field research conducted at two sites each year during 2014 to 2016 in each state with the participating university, with a third site in Missouri in 2016. A total of 49 site-years of data from environments ranging in soil productivity and weather conditions were collected. Treatments included N fertilizer rates between 0 and 315 kg N ha^{-1} applied either all at-planting or were split, where 45 kg N ha^{-1} was put on at-planting, and additional fertilizer N was applied at the V9 corn growth stage. All states followed a similar protocol for plot research implementation including weather data collection, soil, and plant sample timing and collection methodology, N application timing, N source, and N rates as described in Kitchen et al. (2017).

Nitrogen Recommendation Tools and EONR

Three unique tools were selected based on their previously identified ability to predict EONR as discussed in chapter two. They are as follows: 1) Farmer's NR, 2) Indiana yield goal (IN YG), and 3) active-optical canopy reflectance sensing. The farmer's NR was the fertilizer N rate that the farmer or research station applied to the field site under ideal corn growing conditions. The recommended N rate using the IN YG method (Vitosh et al., 1995) was calculated as follows:

$$IN\,YG = [-30 + 1.52 \times YG - N_{credit}] \qquad [1]$$

where YG is the yield goal or expected yield for that field. The expected yield was determined based on a five-year grain yield county average and modified to match the site's productivity as described in chapter two. The N_{credit} is valued as 34 kg N ha^{-1} for corn following soybean. Canopy reflectance sensing was evaluated using the Holland and Schepers algorithm with reflectance measurements taken at ~V8-V10 corn development stage using the RapidSCAN CS-45 (Holland Scientific, Lincoln NE, USA). The Holland and Schepers algorithm (Holland and Schepers, 2010) was used to calculate an N fertilizer recommendation derived from these reflectance measurements. This algorithm is based on a sufficiency index calculated using measurements from both well-fertilized corn (“N-Rich”) and minimally-fertilized (“target”) corn:

$$SI = \frac{VI_{Target}}{VI_{N-Rich}} \tag{2}$$

where SI is the sufficiency index; VI_{Target} is the vegetative index obtained from averaging measurements from all plots that received 45 kg N ha^{-1} at-planting and where a top-dress fertilizer was to be applied, and $VI_{N\text{-}Rich}$ is the vegetative index obtained by averaging all plots for two of the high N treatments (225 and 270 kg N ha^{-1} applied all at-planting). The NDRE vegetative index was calculated using the red-edge (730 nm; RE) and near-infrared (780 nm; NIR) wavelengths as shown:

$$\mathrm{NDRE} = \frac{NIR-RE}{NIR+RE} \tag{3}$$

Fertilizer N recommendations were then calculated as described in Holland and Schepers (2010) as follows:

$$N_{Rec} = \left(MZ_i * N_{Opt} - N_{PreFert} - N_{CRD} + N_{Comp}\right) * \sqrt{\frac{(1-SI)}{\Delta SI}} \tag{4}$$

where N_{Rec} is the calculated N fertilizer recommendation; MZ_i is a scaling value ($0 \geq MZ_i \leq 2$) used to adjust the N recommendation based on areas of high or low yield performance; N_{Opt} was the base N rate, which is determined by the farmer; $N_{PreFert}$ is the amount of N already applied prior to sensing; N_{CRD} are N credits associated with the previous crop, NO_3–N in irrigation water, manure, or residual NO_3–N; N_{Comp} is an optional compensation factor for growth limiting conditions; SI is the sufficiency index, and ΔSI is a value to define the response range. For this analysis, MZ_i was left as the default value of 1.0, N_{opt} was set as the recorded farmer's NR for each site, and $N_{PreFert}$ = 45 kg N ha^{-1}. With no supportive information relative to N_{CRD} and N_{Comp}, these two parameters were set to zero for all sites. The recommended value of 0.30 was used for ΔSI, which provides a response range between the measured vegetative index value between 0.70 and 1.00.

Grain yield in response to N fertilizer treatments was used to calculate the EONR on a site level as described in Kitchen et al. (2017), using proven quadratic or quadratic-plateau modeling methods (Cerrato and Blackmer, 1990; Scharf et al., 2005). Economic optimal N rate values were calculated for all N fertilizer applied at-planting, and N split applied between planting and a single top-dress. For this study, the prices of N and grain were set at \$0.88 kg N^{-1} and \$0.158 kg $grain^{-1}$ (equivalent to \$0.40 lbs N^{-1} and \$4.00 bu^{-1}). The EONR was set to not exceed the maximum N rate (315 kg N ha^{-1}). For five of the seven irrigated sites, where the amount of N applied through irrigation was above 12 kg N ha^{-1} (ranging from 15 – 43 kg N ha^{-1}), this amount was added to the EONR value. The EONR was used as the standard by which each of the N recommendation tools was compared. For 19 of the 49 sites, the at-planting and split EONR values were found statistically (P=0.05) to be same, within \$2.50 ha^{-1} of each other. Thus for these the EONR used was the average of the two timings. This approach was also consistent with previous separate analysis using this same dataset (Bandura, 2017).

Modeling Scenarios

Ninety distinct modeling scenarios [8 algorithms × 2 types of data (explained below) × 2 interaction types (explained below) × 3 N recommendation tools – 6 excluded modeling scenarios (explained below)] were developed to model the difference between a tool N recommendation and EONR and soil and weather information. These included the following eight algorithms: 1) stepwise using Akaike's information criteria (Yamashita et al., 2007), 2) ridge regression (McDonald, 2009), 3) Lasso, 4) elastic net regression (Zou and Hastie, 2005), 5) principal component analysis (PCA; Abdi and Williams, 2010), 6) PLS, 7) Bayesian Lasso (Park and Casella, 2008), and 8) random forest (Grömping, 2009). Each of these algorithms was evaluated with a complete and a reduced dataset. The complete dataset contained all available soil and weather variables (Table 1), while the reduced dataset excluded variables that were highly correlated ($|r| > 0.85$) with each other (Table 2; Fig. 1). Correlated variables were determined by using pair-wise correlations, with variables having the highest mean absolute correlation removed from the dataset as identified with the findCorrelation function from the R 'caret' package (Kuhn, 2017). For both the complete and reduced datasets each of the algorithms were evaluated with and without 2-way-interaction terms. Each of these modeling scenarios was repeated for each of the three N recommendation tools. Six modeling scenarios associated with using the stepwise regression with two-way interaction terms were not included in this evaluation due to the process being computationally slow and often resulting in errors.

Fitting Algorithm Models

All algorithms were fit using the ‘caret’ package using R Statistical Software (R Core Team, 2016). For some of the algorithms, additional parameters needed to be tuned for optimal performance. The tuning procedure was done using a tenfold cross-validation repeated five times, where for each fold of the cross-validation the data were split randomly into ten folds. Nine of the folds were selected as a training dataset to fit a model. The training dataset was used to fit multiple models to determine the optimal tuning parameter values. For example, to optimize the elastic net both the alpha and lambda parameters needed to be optimized. A model was fit to each unique combination of 5 alpha, and 100 lambda values, resulting in a total of 500 models fit on each fold of the training dataset. Each of these models was then evaluated by calculating a root mean square error (RMSE) value by comparing the predicted to the actual values of the 10th fold left out of the training dataset. This was repeated until each fold was used as the testing dataset. The overall process was then repeated five times to provide a total of 50 unique testing folds and resulting in 25,000 elastic net models (50 folds × 500 tuning parameter models). The resulting RMSE values were averaged across tuning parameter combinations. The best tuning parameter was selected as the one with the lowest average RMSE.

The range of tuning parameters differed for each algorithm. The ridge regression, lasso, and elastic net all utilize lambda parameters ranging from 0.001 to 25 in increments of 0.25. The alpha parameter was maintained constant for the ridge regression and lasso but ranged between 0 and 1 in increments of 0.25. For these three models, the best tuning parameters were determined using a coordinate descent algorithm (Friedman et al., 2010).

The Bayesian Lasso's sparsity threshold ranged from 0 to 1 in increments of 0.10, where a sparsity value of .50 indicated that at least half of the posterior estimates used were nonzero (Kuhn, 2017). The Gibbs sampling algorithm was used to determine the best sparsity value (Park and Casella, 2008). For the random forest algorithm, the number of variables evaluated at each split was determined by tuning between 1 and 25 variables for the dataset with complete interactions, and 1 and 10 when no interactions were present.

All explanatory variables were preprocessed first by normalizing the data by subtracting the mean and dividing by the standard deviation of each variable. Preprocessing was used for all algorithms except the random forest.

For each modeling scenario the response variable was the difference between each tool's N recommendation and the EONR value for each site as follows:

$$Tool_{Diff} = Tool_{N\ Rec} - EONR \quad [5]$$

where EONR was calculated using N treatments applied all at-planting (Farmer's NR and IN YG) or with split N treatments (canopy reflectance sensing). Explanatory variables included measured physical and chemical soil properties and measured weather information. Soil properties were collected by sampling 1.2 m soil cores from each of the sites and analyzing each pedological soil horizon for texture, bulk density, pH salt, pH water, CEC, total N, total carbon, inorganic carbon, organic carbon, and organic matter as (Table 1). Soil properties were then depth weighted across three different depths of 0-0.30, 0-0.60, and 0-0.90 m. Weather data were collected using on-site weather stations (HOBO U30 Automatic Weather Station; Onset Computer Corporation, Bourne, MA). Daily values were calculated for the maximum and minimum temperature and precipitation. These values were then used to calculate a cumulative precipitation, growing degree days, corn heat units, Shanon’s diversity index of precipitation, and abundantly and well-distributed rainfall as described by Tremblay et al. (2012), in increments of either 30 days before planting up to the date of planting and from the date of planting to the time of sensing (Table 1).

Assessing Algorithm Performance

Each algorithm’s performance was assessed using the out-of-sample error, the number of variables in the final model, and the performance of each N recommendation tool incorporating each algorithm's model. The out-of-sample error was calculated using the same cross-validation folds that were used to tune each algorithm’s parameters. An RMSE was computed on the testing fold using the predictive models developed with each training dataset. A total of 50 RMSE values was calculated for each algorithm, one for each cross-validation testing dataset. The same cross-validation folds were used for all modeling scenarios to compare across algorithms accurately. To determine significant differences between algorithms, an ANOVA was conducted using the 50 RMSE values as the response variable and the algorithm and N recommendation tool (Farmer NR, IN YG, canopy reflectance sensing) as the explanatory variables. Significance mean separation between algorithms was determined using a Tukey HSD ($\alpha = 0.05$).

Secondly, the total number of variables selected by each algorithm was determined using the varImp function in the R ‘caret’ package. Determining which variables were important varied depending on the algorithm. For regression-based algorithms (stepwise, Lasso, ridge regression, and elastic net) the varImp function calculates the absolute value of the t-statistic for each parameter in the model, with higher t-statistic values indicating higher importance. While for PLS, the varImp function is based on the weighted sums of the absolute regression coefficients. The PCA was determined as the number of variables used in the principal component that explained the most variability. Random forest uses the mean square error (MSE) for both the out-of-bag prediction accuracy for each tree constructed and the out-of-bag prediction accuracy for each predictor variable permuted. The differences between the tree and predictor variable out-of-bag MSEs are averaged and normalized using the standard error. Additional details can be found in the caret vignette under "14.1 Model Specific Metrics" (Kuhn, 2017).

Lastly, each N recommendation was adjusted by taking the original tool recommendations and subtracting the predicted values generated using the model parameters as follows:

$$Tool_{adj} = Tool_{Diff} - EONR \qquad [4]$$

This adjustment to each tool was repeated for each modeling scenario for a total of 30 (8 variable selection methods × 2 data types × 2 interaction types – 2 excluded modeling scenarios) newly adjusted N recommendations. Each adjusted tool was then compared to EONR to determine if there was an improved performance of the tools at predicting EONR. This was accomplished by calculating both a coefficient of determination and RMSE for each adjusted tool. The coefficient of determination was calculated using simple linear regression with EONR as the response variable and the adjusted tool as the explanatory variable. The RMSE was calculated based on the difference between the adjusted tool and EONR values. Improvement for the adjusted tool was determined by comparing the r^2 and RMSE similar values obtained from the unadjusted tool.

RESULTS AND DISCUSSION

Algorithm Performance: Model Accuracy and identifying Important Variables

There was a significant two-way interaction ($P < 0.001$) when comparing the out-of-sample errors across all algorithms and tools (Fig. 2 – 4). For all N recommendation tools, the stepwise regression's out-of-sample error using the complete dataset was significantly greater than all other algorithm types including using the stepwise regression with all multicollinearity removed (Fig. 2 – 4). Apart from the one modeling scenario with the stepwise regression, there was no significant difference between the out-of-sample error for the other algorithms or modeling scenarios.

The number of important variables identified in the final models varied based on the type of algorithm. For all modeling scenarios, the Lasso and elastic net resulted in the fewest number of variables in the final model. Stepwise regression, Ridge regression, PCA, PLS, Bayesian Lasso, and Random Forest maintained all or close to all of the variables in their final model (Table 3).

Determining the algorithm that best incorporates soil and weather information into an N recommendation tool depends on the investigative priority. Algorithms can be chosen based on either optimizing accuracy or resulting in a parsimonious model. Tools that select and utilize numerous variables could improve the accuracy of the model, such as using the random forest. However, from an agronomic standpoint, algorithms that select fewer variables have the advantage of being easier to interpret. Furthermore, implementing a model that requires more variables increases costs associated with measurement, sampling, and analysis. From this standpoint utilizing the Lasso or elastic net under any modeling scenario would be ideal as there was no significant difference in modeling accuracy and they produced the most parsimonious model (Table 3, Fig. 2 – 4). Between these two algorithms, it has been shown that the elastic net is more robust and often accurately selects more true variables (Bien et al., 2013; Lu and Petkova, 2014).

Ideally, an algorithm that can select for variables using a dataset with highly correlated variables and multiple interaction terms would minimize the amount of data processing required. The ridge regression, PCA, PLS, Bayesian Lasso and random forest algorithms have been identified as suitable algorithms for when multicollinearity and interaction terms are included in the model (Geladi and Kowalski, 1986; Grömping, 2009; Abdi and Williams, 2010; Lu and Petkova, 2014). However, these algorithms did not produce a parsimonious model. To improve these algorithms to have a more parsimonious model the number of variables can be prefiltered before modeling. The method used in this research for lowering variable numbers based on correlation tests was successful, and the results were promising but still not more parsimonious than the elastic net. The ridge regression, PCA, PLS, Bayesian Lasso and random forest produced a more parsimonious model without reducing their predictive accuracy (Table 3). In contrast, to the Lasso and elastic net, these algorithms still retained more variables in the final model.

Results about which parameters were selected and their importance for explaining the variability around EONR will be addressed in chapter 4.

Adjusting Tools with Soil and Weather Information

Removing Multicollinearity

There was a difference in the observed improvement between the complete and reduced dataset based on the algorithm type and N recommendation tool (Table 4). For both the stepwise and ridge regression algorithms, there was less improvement for all three tools using the reduced dataset compared to the complete dataset (r^2 increased $\geq$ 0.10 and RMSE decreased $\geq$7). For the elastic net, there was an improvement in which removing multicollinearity improved the Farmer NR. Additionally, the PCA improved the Farmer NR and canopy reflectance sensing. These improvements occurred when all interaction terms were excluded (Table 4). For the remaining modeling scenarios, there was no improvement by first eliminating multicollinearity.

The Lasso algorithm resulted in the fewest number of variables in the final model regardless of modeling scenario. However, modeling with highly correlated variables have been found to quickly oversaturate the Lasso algorithm, especially when the number of variables exceeds the number of observations (Zou and Hastie, 2005). Under such conditions, the Lasso randomly selects one variable from a group of highly correlated variables and disregards the rest (Efron et al., 2004; Bondell and Reich, 2008). This can result in the algorithm selecting variables that are not valid predictors of the response variable (Lu and Petkova, 2014). However, when accounting for multicollinearity by removing variables, there was a minimal change in the number of variables in the final model. In both modeling scenarios with and without multicollinearity, the Lasso was only helpful in improving N recommendations using canopy reflectance sensing. The final Lasso model for canopy reflectance sensing had more variables than the Lasso models for the Farmer NR and IN YG. For these tools, it seems that selecting too few variables reduces the algorithm's ability to capture the most amount of variability affecting EONR, resulting in no or a limited improvement to the N recommendation tool.

The elastic net deals with these issues of oversaturation or selecting too few variables by balancing the Lasso and ridge regression methods. For most of the modeling scenarios, the elastic net either selected the same or up to eight more variables than the Lasso algorithm. The selection of these additional variables did not decrease the accuracy of the elastic net algorithm. However, it did not substantially improve the performance of N recommendation tools for the majority of modeling scenarios. The only improvement occurred was with the Farmer's NR after multicollinearity was removed, where the r^2 for the elastic net was 0.24 ($P < 0.001$) compared to 0.03 ($P = 0.25$) for the Lasso. Comparable, research utilizing the Lasso and elastic net for selecting optimal testing parameters for Autism, showed they performed the same, but both were optimized when there was no multicollinearity between variables (Lu and Petkova, 2014).

Utilizing the PCA to improve the Farmer NR and canopy reflectance sensing showed greater improvement after removing multicollinearity. The presence of multicollinearity has been shown not to affect PCA, as it can efficiently reduce variables to where multicollinearity is no longer an issue. One study showed that PCA effectively identified five soil properties as a subset of 20 correlated soil variables to predict grain yield (Jagadamma et al., 2008). However, PCA has also been found to select variables that are not well related to the response variable (Abdi and Williams, 2010). This issue could be minimized by reducing the number of variables in the final model.

Interaction Terms

There were a few modeling scenarios in which including the interaction terms improved a tool's performance compared to excluding the interaction terms (r^2 increased

≥ 0.10 and RMSE decreased ≥7). This occurred for the Farmer's NR using the ridge regression without removing multicollinearity (Table 4). However, there were two instances where including the interaction terms decreased the performance of the tools. This occurred for the elastic net and PCA after having first removed multicollinearity. For the remaining modeling scenarios, there was no added benefit observed by including the two-way interactions.

The observed decrease in performance using the elastic net and PCA is contrary to what has been reported by others (Wu et al., 2009; Wang et al., 2011). However, elastic net, similar to Lasso, could be affected by oversaturation resulting in more two-way interaction selected and resulting in more penalization of main effects which could be of more importance (Bien et al., 2013). Likewise, PCA has been found to select variables that are not well related to the response variable (Abdi and Williams, 2010). It is more likely that with additional interaction terms in the model, the likelihood of selecting for unimportant variables could increase.

The Best Algorithm for Improving EONR Prediction

Algorithms did not improve the N recommendation tools' performance equally. The random forest model showed the most improvement for predicting EONR regardless of modeling scenario. With this algorithm, all adjusted tools' relationship with EONR improved the r^2 values from ≤ 0.13 to ≥ 0.82 (Table 4). The RMSE values were also some of the lowest and ranged between 33 and 43 kg N ha^{-1}. The stepwise regression was the only algorithm that was able to adjust the N recommendation tool to where the r^2 values were ≥ 0.86 ($P < 0.001$), and the RMSE was as low as 21 kg N ha^{-1}. However, the stepwise regression only showed this level of improvement when using the complete dataset with highly correlated variables. This is indicative of overfitting the model, and therefore the final model would likely fail when applied to other datasets. Under conditions where multicollinearity was removed, the stepwise regression did not have as great a performance, but it was no less than the other algorithms.

The overall performance of tools adjusted using each of the algorithms depends on how well the unadjusted tool was initially related to EONR. The IN YG, which had a negative linear relationship with EONR, showed minimal improvement with five and six of the algorithms with and without multicollinearity, respectively (Table 4). An improvement that was observed with IN YG when adjusted with soil and weather information was that its predicted N values were no longer negatively related to EONR. Nevertheless, these values were also not significantly associated with EONR. When evaluating the IN YG without removing multicollinearity, the ridge regression and random forest were the only algorithms able to improve the IN YG to where it had a significant and positive linear relationship with EONR.

The Farmer's NR, which unadjusted was not related to EONR, showed greater improvement when soil and weather variables were incorporated with many of the algorithm types than the IN YG. Still, not all algorithms were able to improve the tool's relationship with EONR. The algorithms that did positively impact the Farmer's NR performance (besides stepwise and random forest) still had a weak association with EONR ($r^2 \leq 0.47$) and a high RMSE value ≥ 60 kg N ha^{-1} (Table 4).

Canopy reflectance sensing, which unadjusted had a significant positive linear relationship with EONR, was improved when using any of the algorithms. Apart from the random forest algorithm and stepwise regression, the ridge regression showed the most improvement using the complete dataset (Table 4). A slight decrease in improvement was observed with all the other algorithms; however, these remaining algorithms showed similar improvement with r^2 values between 0.24 and 0.44 and RMSE values between 63 and 71 (Table 4).

Another important factor for choosing an algorithm is the ease of interpretation. For many of the regression-based algorithms, the interpretation can be straightforward. For instance, the stepwise, ridge regression, Lasso, and the elastic net can return coefficients for the parameters, allowing a researcher to compare the magnitude and direction (i.e., positive or negative) of the relationship between each parameter and the response variable. This makes these algorithm types very compelling. The ridge regression can be the most difficult to interpret out of these regression-based algorithms as it keeps all parameters in the final model.

In contrast to regression-based algorithms, the PCA, PLS, and random forest algorithms are much more difficult to interpret. For example, the PCA final model is made up of the best principle components that explain the majority of variability in the explanatory variables. However, additional steps are required to determine which variables were used to create those principal components. To explain results data must be displayed by comparing multiple principal components using biplots or scree plots. This has been done successfully in many agricultural datasets however the interpretation is complicated compared to regression-based algorithms (Mueller et al., 2017; Zuber et al., 2017). Similar graphical procedures are required for the PLS algorithm. Apart from the difficulty of interpreting these algorithms, they both did not perform any better than the ridge regression, lasso, or elastic net in the majority of cases.

Compared to the PCA and PLS algorithms, the random forest best improved all three N recommendation tools. This algorithm was best able to incorporate complex interaction and highly correlated variables since it uses nonparametric methods to identify relationships between explanatory and response variables (Archer and Kimes, 2008; Strobl et al., 2008). The ability to model complex interactions could be helpful as soil and weather interaction terms have been found to explain EONR or a yield response (Schröder et al., 2000; Shanahan et al., 2008; Shahandeh et al., 2011; Tremblay et al., 2012). However, like PCA the interpretability of the random forest is complicated as it is the result of an ensemble of hundreds of decision trees. The random forest can be interpreted by using the most important explanatory variables identified to capture the most variability in the response variable. Determining the specific effects of each parameter requires additional steps which include complex graphical interpretations (Meinshausen, 2011; Welling et al., 2015, 2016). A possible method is to filter out unimportant variables selected using another method (correlation tests or elastic net). It was observed that the accuracy of the model was not reduced by decreasing the number of variables from 1080 to 10.

Deciding on how best to incorporate soil and weather information into N recommendation tools may require the use of multiple algorithms. Selecting the best algorithm could be accomplished based on the simple initial linear relationship the tool had with EONR. Tools that are significant but negatively related to EONR would best be improved by utilizing the random forest or ridge regression algorithms. Whereas, tools that are not related to EONR, like the Farmer's NR could best be explained using the elastic net, after removing multicollinearity. Lastly, tools that showed to be already significantly and positively related to EONR could best be improved using any one of the algorithm types. However, for ease of interpretability, the elastic net would be the optimal tool for removing multicollinearity but keeping interaction terms.

CONCLUSIONS

This study compared eight algorithm types for incorporating soil and weather data into three different N recommendation tools. Random forest models were best able to improve all three N recommendation tools however at the expense of including an extensive number of variables. Pre-filtering the number of variables by removing multicollinearity did not decrease the accuracy of this algorithm regardless of the N recommendation tool. However, to fully interpret results would require additional steps for many of these algorithms. On the other hand, penalization based algorithms such as Lasso or elastic net produced a parsimonious model that could easily be interpreted. The Lasso was observed to have the least amount of variables in the final model, which did not help in maximizing N recommendation tool's performance. In contrast, the elastic net allowed for more variables in the final model and showed slight improvements for the adjusted N recommendation tools. The elastic net did not work for improving all N recommendation tools but was shown to work best after multicollinearity, and two-way interaction terms were removed from the model. From an agronomic point of view, the elastic net was best suited for the desired results of improving N recommendation tools with soil and weather information.

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Table 1. Weather and soil variables used in the complete dataset with calculations, methods, and associated citations. The period of time used to calculate the weather variables are found in Table 2.

	Complete Dataset		
Variables	**Calculations and Sample Depths**	**Method**	**References**
Weather			
Precipitation (PPT)	Sum of daily rainfall, mm.	Tipping bucket[§]	(Tremblay et al., 2012)
Corn heat units (CHU)	Σ(Ymax + Ymin)/2; Ymax and Ymin are the daily maximum and minimum temperatures, ^{o}C.	Temperature sensor[§]	(Tremblay et al., 2012)
Growing degree day (GDD)	Σ((Ymax + Ymin)/2)-T_{base}; Ymax, Ymin, T_{base} are the daily maximum, minimum, and base temperatures, respectively. T_{base} = 10^{o}C.	Temperature sensor	(Tremblay et al., 2012)
Shanon diversity index (SDI)	[-Σpi ln(pi)]/ln(n); where pi = Rain/PPT (daily rainfall relative to total rainfall in a given time; n = total number of days.	Tipping bucket	(Tremblay et al., 2012)
Abundant and well-distributed rainfall (AWDR)	SDI × PPT	Tipping bucket	(Tremblay et al., 2012)
Soil			
Clay	0-30, 0-60, 0-90 cm	Pipette	Soil Survey Staff (2014) 3A1
Sand	0-30, 0-60, 0-90 cm	Pipette	Soil Survey Staff (2014) 3A1
Silt	0-30, 0-60, 0-90 cm	Pipette	Soil Survey Staff (2014) 3A1

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Table 1 (Continued.)

Parameter	Complete Dataset Calculations and Sample Depths	Method	References
Cation exchange capacity	0-30, 0-60, 0-90 cm	Ammonium acetate	Soil Survey Staff (2014) 4B1a1a1a1a-b1
Total N	0-30, 0-60, 0-90 cm	Dry combustion	Soil Survey Staff (2014) 4H2a1
Total carbon (C)	0-30, 0-60, 0-90 cm	Dry combustion	Soil Survey Staff (2014) 4H2a1
Total organic C	0-30, 0-60, 0-90 cm	Dry combustion	Nelson and Sommers (1996)
Total inorganic C	0-30, 0-60, 0-90 cm	Difference between Total C and total organic C	
Organic matter	0-30, 0-60, 0-90 cm	Loss-on-ignition	Soil Survey Staff (2014) 5A
pH (Salt)	0-30, 0-60, 0-90 cm	pH Meter	Soil Survey Staff (2014) 4C1a1a2
pH (Water)	0-30, 0-60, 0-90 cm	pH Meter	Soil Survey Staff (2014) 4C1a1a2
Bulk Density	0-30, 0-60, 0-90 cm	Core	Soil Survey Staff(2014) 3B6a

† Daily temperature and precipitation measured using HOBO weather stations instrumentation (Onset Computer Corporation, Bourne, MA).

Table 2. Variables used by all algorithms to modify three N recommendation tools. Within the table, X indicates parameters used for modeling and blank indicates parameters that were removed due to multicollinearity issues. Dashes indicate not applicable.

Reduced Dataset			
Parameter	**Farmer NR**	**IN YG**	**Canopy Reflectance Sensing**
<u>Weather</u>			
PPT (Planting)†			
PPT (Sidedress)‡	–	–	X
Corn Heat Units (Planting)			
Corn Heat Units (Sidedress)	–	–	X
GDD (Planting)	X	X	X
GDD (Sidedress)	–	–	
SDI (Planting)	X	X	X
SDI (Sidedress)	–	–	X
AWDR (Planting)	X	X	X
AWDR (Sidedress)	–	–	
<u>Soil</u>			
Clay	X (0-90 cm)	X (0-90 cm)	X (0-90 cm)
Sand	X (0-90 cm)	X (0-90 cm)	
Silt			X (0-60 cm)
Cation exchange capacity			
Total N			
Total carbon (C)	X (0-90 cm)	X (0-90 cm)	X (0-90 cm)
Total organic C			
Total inorganic C	X (0-30 cm)	X (0-30 cm)	X (0-30 cm)
Organic matter	X (0-30 cm)	X (0-30 cm)	X (0-90 cm)
pH (Salt)			
pH (Water)	X (0-30 cm)	X (0-30 cm)	X (0-30 cm)
Bulk Density	X (0-30 cm)	X (0-30 cm)	X (0-30 cm)

† Planting indicates data used 30 days prior to planting up to the date of planting
‡Sidedress indicates data used from the date of planting up to the date of sidedress

Table 3. The number of soil and weather variables identified as important for adjusting three different N recommendation tools using eight different algorithms with four different modeling scenarios. Models were fit with and without two-way interactions terms using either a complete dataset with all soil and weather variables or a reduced dataset with highly correlated variables removed (r > |0.85|).

	Complete Dataset			**Reduced Dataset**		
	Farmer NR	**IN YG**	**Canopy Reflectance Sensing**	**Farmer NR**	**IN YG**	**Canopy Reflectance Sensing**
Algorithm	**Number of Important Variables**			**Number of Important Variables**		
Stepwise	39	39	44	9	9	12
Ridge	40	40	45	9	9	12
+ Interactions	860	860	1080	54	54	90
Lasso	2	4	7	1	2	5
+ interactions	2	3	4	3	2	7
Elastic Net	2	7	15	9	2	8
+ Interactions	2	8	12	3	2	7
PCA	45	45	45	9	9	9
+ Interactions	1080	1080	1080	54	54	54
PLS	40	40	45	9	9	12
+ Interactions	860	860	1080	54	54	90
Bayesian Lasso	39	39	44	9	9	12
+ Interactions	39	39	44	9	9	12
Random Forest	40	40	45	9	9	12
+ Interactions	860	860	1080	54	54	90

Table 4. The accuracy of each N recommendation tool compared to EONR that was unadjusted and adjusted with soil and weather variables as determined by each of the eight algorithms. Models were evaluated using a complete dataset or reduced dataset (multicollinearity removed) with and without 2-way interactions. The coefficient of determination was measured from a simple linear relationship between each tool and EONR with the corresponding relationship marked in parenthesis: (+) positive linear relationship, (-) negative linear relationship, and no parenthesis after the r^2 value is non-significant ($\alpha = 0.10$). The RMSE was calculated from the difference between a tool's N recommendation and EONR.

	Complete Dataset						**Reduced Dataset**					
Model Adjustment	**Farmer NR**		**IN YG**		**Canopy Reflectance Sensing**		**Farmer NR**		**IN YG**		**Canopy Reflectance Sensing**	
	r^2	RMSE	r^2	RMSE	r^2	RMSE	r^2	RMSE	r^2	RMSE	r^2	RMSE
Unadjusted	*0.01*	*88*	*0.10* (-)	*127*	*0.13* (+)	*85*	*0.01*	*88*	*0.10* (-)	*127*	*0.13* (+)	*85*
Stepwise	0.94 (+)	21	0.86 (+)	31	0.95 (+)	41	0.30 (+)	68	0.03	90	0.41 (+)	63
Ridge	0.32 (+)	67	0.08 (+)	83	0.66 (+)	52	0.27 (+)	70	0.03	89	0.43 (+)	62
+ Interactions	0.47 (+)	60	0.14 (+)	78	0.58 (+)	56	0.23 (+)	71	0.01	91	0.38 (+)	64
Lasso	0.03	82	0.00	92	0.40 (+)	63	0.03	82	0.00	92	0.39 (+)	63
+ Interactions	0.06 (+)	80	0.00	91	0.32 (+)	66	0.04	81	0.00	93	0.44 (+)	61
Elastic Net	0.03	82	0.00	91	0.39 (+)	63	0.24 (+)	71	0.00	92	0.38 (+)	64
+ Interactions	0.06 (+)	80	0.00	91	0.34 (+)	65	0.04	81	0.00	93	0.43 (+)	62
PCA	0.10 (+)	78	0.01	98	0.24 (+)	69	0.21 (+)	72	0.00	93	0.35 (+)	65
+ Interactions	0.09 (+)	78	0.00	95	0.27 (+)	68	0.06 (+)	80	0.00	94	0.23 (+)	70
PLS	0.19 (+)	74	0.02	93	0.32 (+)	65	0.22 (+)	73	0.02	92	0.38 (+)	63
+ Interactions	0.12 (+)	76	0.01	94	0.30 (+)	66	0.20 (+)	74	0.02	94	0.34 (+)	65
Bayesian Lasso	0.14 (+)	76	0.01	95	0.28 (+)	68	0.07 (+)	79	0.04	99	0.22 (+)	71
+ Interactions	0.09 (+)	78	0.00	93	0.29 (+)	67	0.15 (+)	75	0.00	95	0.31 (+)	67
Random Forest	0.85 (+)	38	0.87 (+)	33	0.90 (+)	42	0.84 (+)	39	0.83 (+)	37	0.90 (+)	43
+ Interactions	0.82 (+)	40	0.86 (+)	35	0.91 (+)	44	0.83 (+)	41	0.82 (+)	38	0.91 +)	43

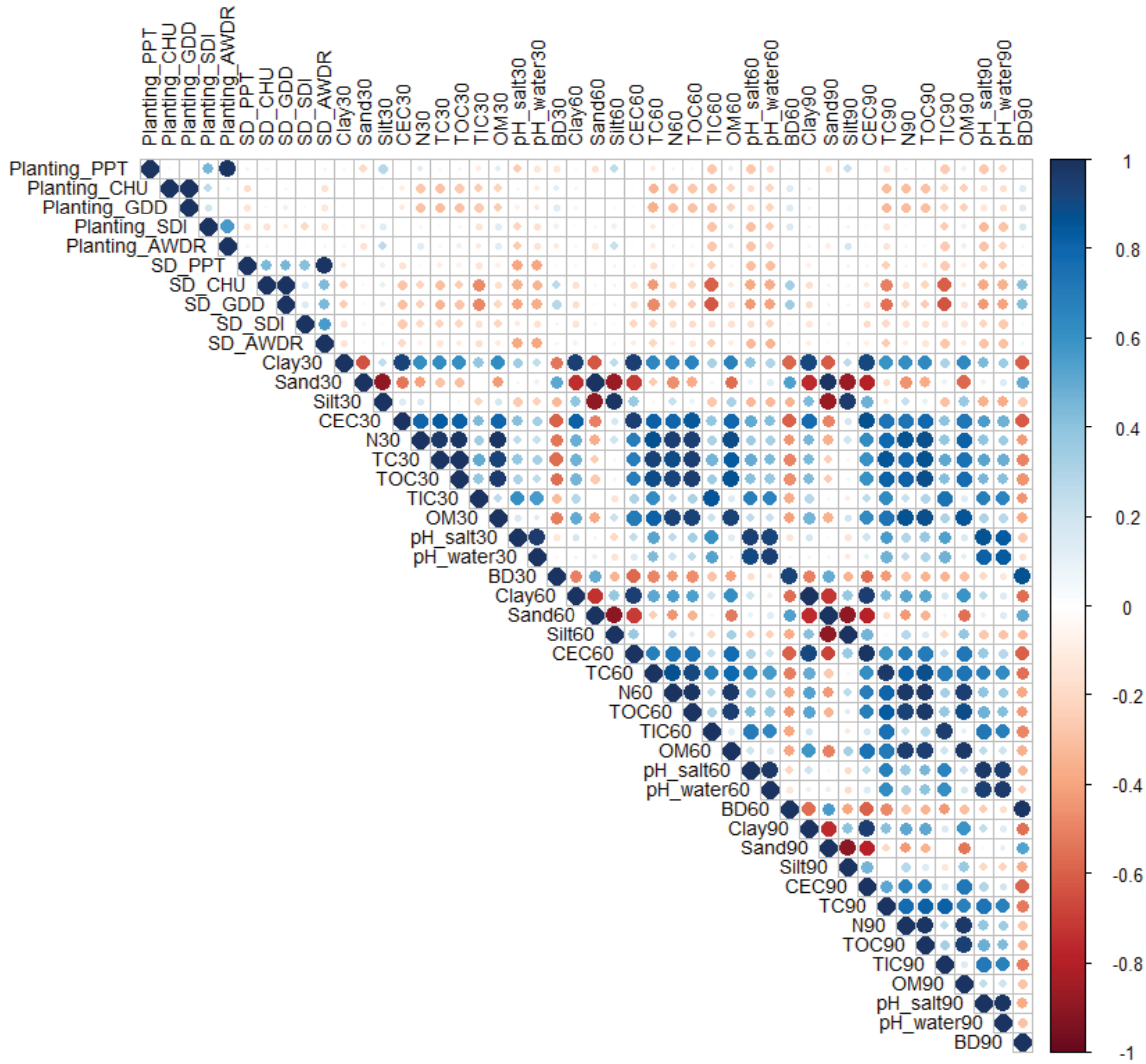

Fig. 1. Correlation matrix of variables that were used for algorithm adjustment of N recommendation tools. The color intensity and size of the circles is proportional to the correlation coefficients. Weather variables calculated from 30 days prior to planting up to the date of planting (planting) and from the date of planting to the date of a sidedress N fertilizer application (SD). They include cumulative precipitation (PPT), corn heat units (CHU), Shannon diversity index of precipitation (SDI), and abundant and well-distributed rainfall (AWDR). Soil variables include texture, cation exchange capacity (CEC), total nitrogen (N), total carbon (TC), total organic carbon (TOC), total inorganic carbon (TIC), organic matter (OM), pH with and without salt, and bulk density (BD). Each measurement was average over three separate depth increments of 0-0.30, 0-0.60, and 0-0.90 m. Produced using the “corrplot” R software package (Wei and Simko, 2017).

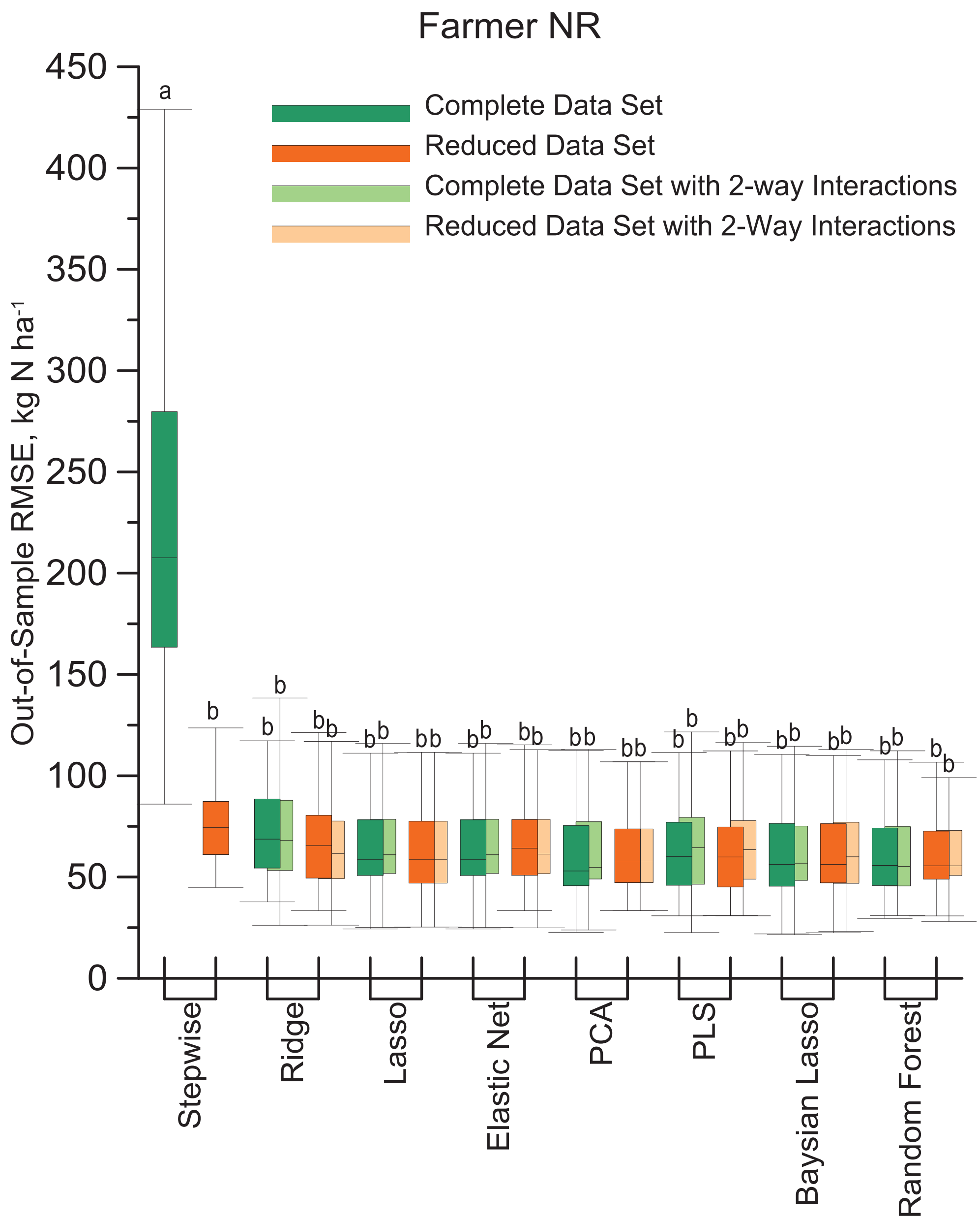

Fig. 2. The out-of-sample RMSEs from eight algorithms that were used for adjusting the Farmer's N rate. The errors were calculated from 5x10 cross-validation folds (totaling 50 RMSE values for each model). Each of the eight models types was used with a complete and reduced dataset (multicollinearity removed) with and without 2-way interactions. The eight models include 1) AIC stepwise linear regression, 2) Ridge regression parameter penalization, 3) least absolute shrinkage and selection operator (Lasso), 4) Elastic Net, 5) Elastic Net and principal component analysis (PCA), 6) partial least square regression (PLS), 7) Bayesian Lasso, and 8) Random Forest. Limits of the box indicate the 1st and 3rd quartile and whiskers indicate 1.5 × IQR. The significance between models is noted by lower case letters, using a Tukey's HSD test ($\alpha = 0.05$).

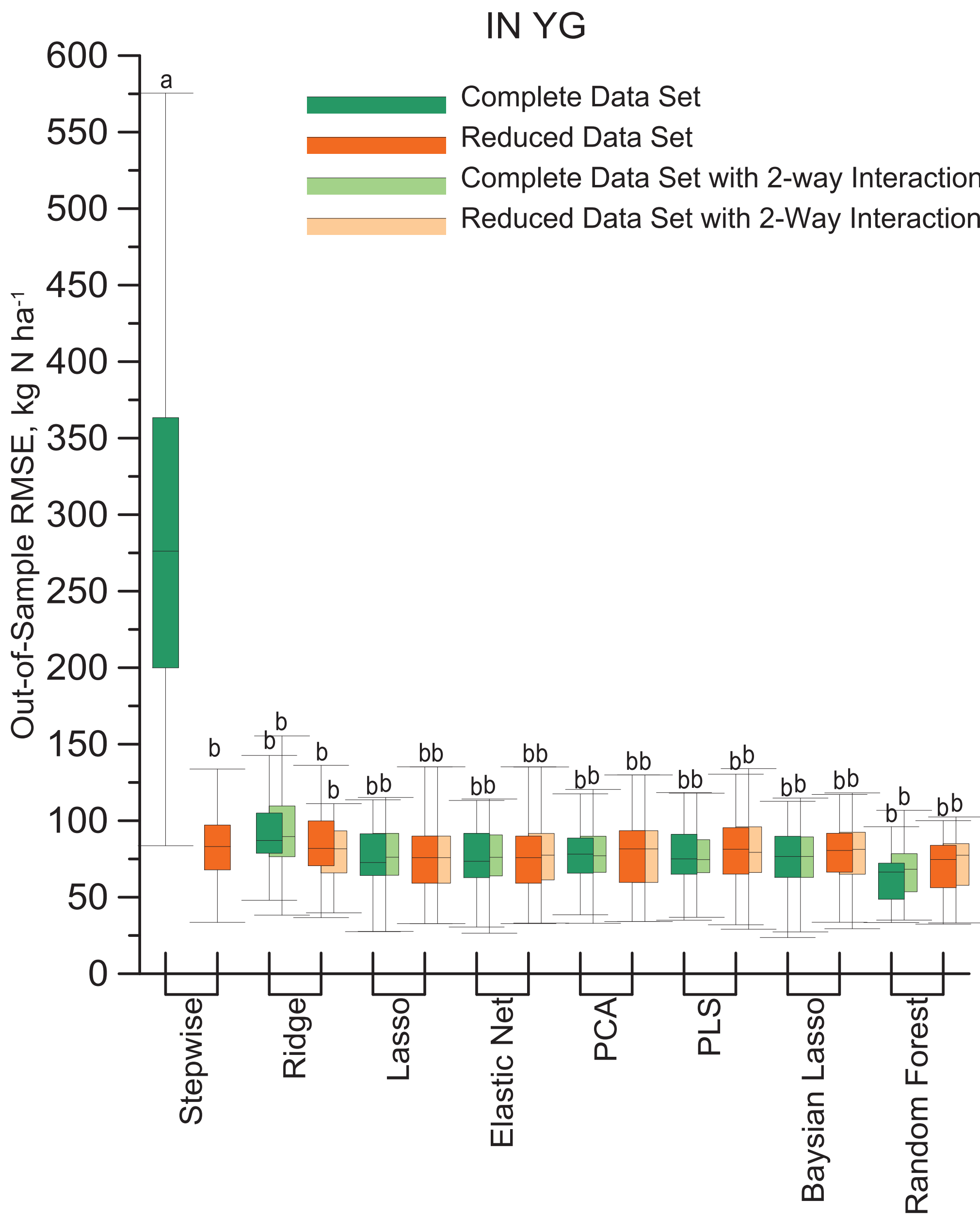

Fig. 3. The out-of-sample RMSEs from eight algorithms that were used for adjusting the Indiana yield goal N recommendation tool. The errors were calculated from 5x10 cross-validation folds (totaling 50 RMSE values for each model). Each of the eight models types was used with a complete and reduced dataset (multicollinearity removed) with and without 2-way interactions. The eight models include 1) AIC stepwise linear regression, 2) Ridge regression parameter penalization, 3) least absolute shrinkage and selection operator (Lasso), 4) Elastic Net, 5) Elastic Net and principal component analysis (PCA), 6) partial least square regression (PLS), 7) Bayesian Lasso, and 8) Random Forest. Limits of the box indicate the 1st and 3rd quartile and whiskers indicate 1.5 × IQR. The significance between models is noted by lower case letters, using a Tukey's HSD test ($\alpha = 0.05$).

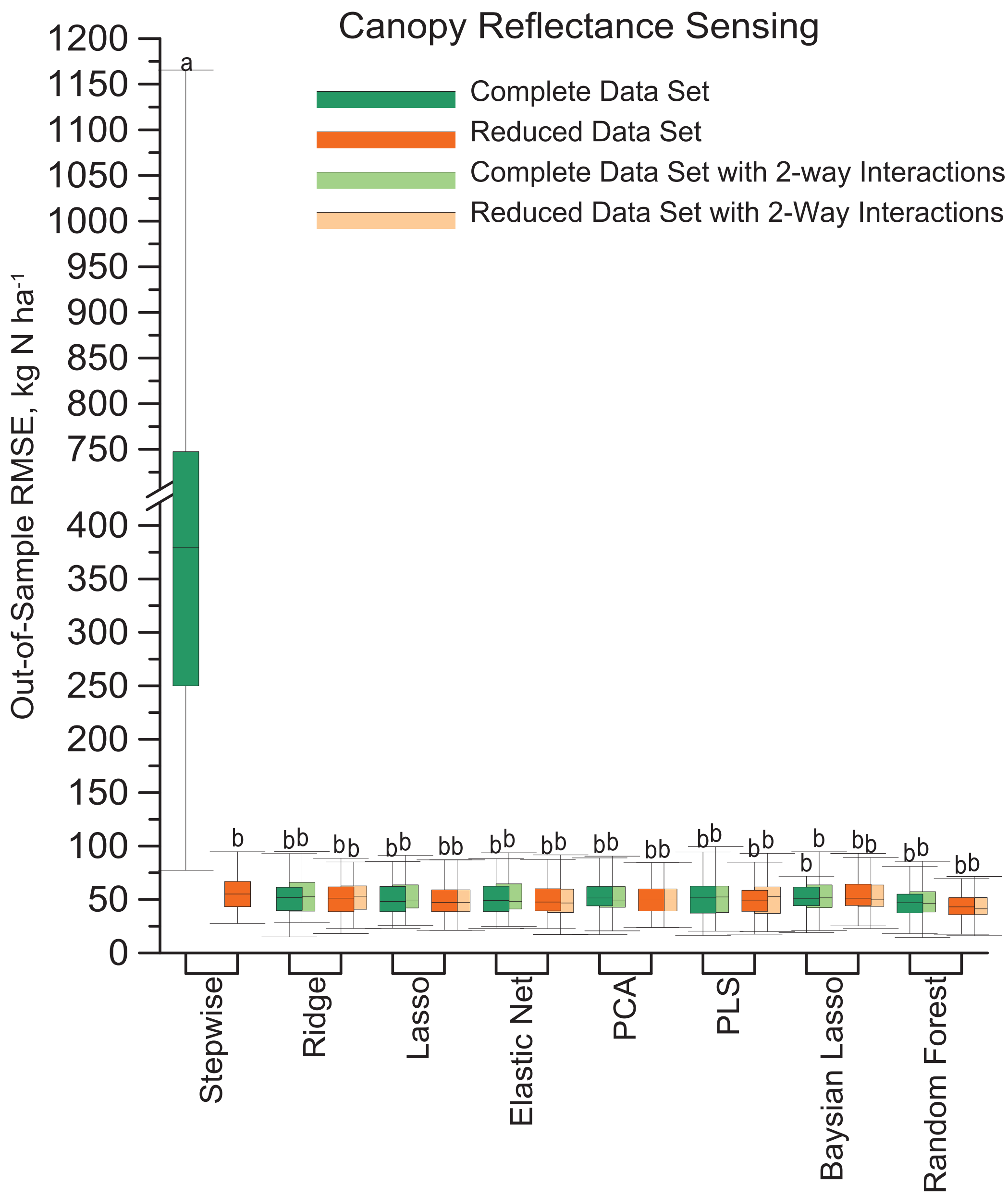

Fig. 4. The out-of-sample RMSEs from eight algorithms that were used for adjusting the canopy reflectance sensing recommendation tool. Each of the eight models types was used with a complete and reduced dataset (multicollinearity removed) with and without 2-way interactions. The eight models include 1) AIC stepwise linear regression, 2) Ridge regression parameter penalization, 3) least absolute shrinkage and selection operator (Lasso), 4) Elastic Net, 5) Elastic Net and principal component analysis (PCA), 6) partial least square regression (PLS), 7) Bayesian Lasso, and 8) Random Forest. Limits of the box indicate the 1st and 3rd quartile and whiskers indicate 1.5 × IQR. The significance between models is noted by lower case letters, using a Tukey's HSD test (α = 0.05).

Chapter 4: Improving Corn Nitrogen Rate Recommendation Tools with Weather and Soil Information

ABSTRACT

Improving corn (*Zea mays* L.) nitrogen (N) fertilizer rate recommendation tools is necessary for improving farmer's profits and one way to mitigate N pollution. Since weather and soil factors have repeatedly been shown to influence crop N need, one method to improve N management is to incorporate additional soil and weather information directly into the N recommendation tool. The objectives of this research were to improve publicly-available N recommendation tools with other soil and weather information. A range of N recommendation tools used at-planting and for split N fertilizer applications were evaluated. Using an elastic net algorithm the difference between each tool's N recommendation and the economically optimum N rate (EONR) was regressed against measured soil and weather information. Tools were then adjusted by subtracting the elastic net regression coefficients of soil and weather variables from the N recommendation tools. Weather parameters most frequently identified as important were the evenness of rainfall calculated 30 days prior to planting up to the date of planting and from planting to the date of sidedness. Soil parameters frequently identified as important included pH (0-30 cm) and total carbon (0-90 cm). Six of the fifteen N recommendation tools showed improvements with a stronger simple linear relationship with EONR (an increase of $r^2 \geq 0.13$). These tools included MRTN for both at-planting and split applications, WI pre-plant soil nitrate test (PPNT), IA pre-sidedress soil nitrate test with 0 kg N ha^{-1} applied at-planting (PSNT 0), IN PSNT 0, and canopy reflectance sensing. The best performance of tools with including soil and weather information

occurred with the IA PSNT 0, canopy reflectance sensing, and MRTN that showed a final $r^2 \geq 0.20$ but ≤ 0.39, and resulted in $\geq 35\%$ but ≤ 55 % of the sites within ± 30 kg N ha^{-1} of EONR. This analysis shows that incorporating soil and weather information could help improve N recommendation tools across the U.S. Midwest. However, while improvements to these publicly-available tools were noteworthy, over half of the variation in EONR is still unexplained. This is not surprising since many other factors that impact soil-crop N dynamics are unconsidered, including factors that occur after a sidedress N application.

INTRODUCTION

One approach used to maximize profits and minimize environmental issues associated with N management in corn is to apply N fertilizer at rates close to the EONR (Hong et al., 2007; Kyveryga et al., 2009; Bandura, 2017). However, EONR is unknown at the time of N application as it is calculated following grain harvest. Moreover, EONR varies considerably within a field and from year-to-year making EONR challenging to estimate (Scharf et al., 2005; Shanahan et al., 2008; Kyveryga et al., 2009). Both the spatial and temporal variability of EONR are driven by environmental, genetic, and management factors. More specifically rainfall distribution, soil texture, soil water-holding capacity, plant genetics, management practices, and grain and fertilizer prices have been shown to influence EONR (Dinnes et al., 2002; Kay et al., 2006; Schmidt et al., 2009; Zhu et al., 2009; Tremblay et al., 2012; Morris et al., 2018). However, many of the current methods used to determine how much N fertilizer to apply do not account for many of these factors.

A few of the publically available N recommendation tools that have been developed incorporate some of the management, soil, and weather factors. A few examples include the yield goal method which was adjusted with a soybean (*Glycine max*) credit if the previous crop was soybean (Stanford, 1973). Other yield goal based methods have also included an estimate of N mineralized by organic matter or a measure of soil nitrate (NO_3–N) before N fertilizer application (Brown et al., 2004; Shapiro et al., 2008). The pre-sidedress nitrate test indirectly measures in-season mineralization rates, and the sufficient N threshold is adjusted based on spring precipitation (Blackmer et al., 1997). The MRTN incorporates multiple yield response studies grouped based on geographical boundaries, soil texture, and climatic conditions to better account for spatial and temporal variability (Sawyer et al., 2006b). Canopy reflectance sensing assesses the color and biomass of corn plants at a very short spatial scale to integrate the plant and soil N status into an N recommendation (Kitchen et al., 2010). Even though these tools indirectly or directly incorporate some aspect of management, soil, and weather into their N recommendation process, these tools have been found to be poorly related with EONR (chapter 2), and therefore are not reliable for making N fertilizer recommendations over the U.S. Corn Belt.

Incorporating additional factors into N recommendation tools, known to affect EONR, could improve them. The incorporation of various weather and soil variables and their interactions improved the relationship of a canopy reflectance sensing derived N recommendation to EONR from an r^2 of 0.14 to 0.43 (Bean et al., 2018). Others showed that including soil-specific information with a pre-plant soil test significantly improved the predictability of optimal N rate (r^2 = 0.92; Vanotti and Bundy, 1999). The objectives of this chapter are to determine if soil and weather information could improve N recommendation tools. This objective was applied to only tools found successful from chapter 2.

MATERIALS AND METHODS

Experimental Design

This research was conducted as a part of a public-private collaboration between DuPont Pioneer and eight U.S. Midwest universities (Iowa State University, University of Illinois Urbana-Champaign, University of Minnesota, University of Missouri, North

Dakota State University, Purdue University, University of Nebraska-Lincoln, and University of Wisconsin-Madison). Each state conducted research on two sites each year during 2014 to 2016, with a third site in Missouri in 2016, totaling 49 site-years. About half the sites were on farmers' fields and the other half on University research stations. All states followed a similar protocol for plot research implementation including site selection, weather data collection, soil sample timing and collection methodology, N application timing, N source, and N rates with specific details described in Kitchen et al. (2017). Treatments included N fertilizer rates between 0 and 315 kg N ha^{-1} applied either all at-planting or split where 45 kg N ha^{-1} was applied at-planting with the remaining fertilizer N applied at the V9 corn developmental stage.

Determining the Economically Optimal Nitrogen Rate

Grain yield in response to N fertilizer treatments was used to calculate the EONR on a site level as described in Kitchen et al. (2017), using proven quadratic or quadratic-plateau modeling methods (Cerrato and Blackmer, 1990; Scharf et al., 2005). Economically optimal N rate values were calculated for all N fertilizer applied at-planting (hereafter referred to as "at-planting"), and N split applied between planting and a single top-dress application (hereafter referred to as "split"). The cost of N was \$0.88 kg N$^{-1,}$ and the price of corn was \$0.158 kg grain^{-1} (equivalent to \$0.40 lbs N^{-1} and \$4.00 bu^{-1}). The EONR was set to not exceed the maximum N rate (315 kg N ha^{-1}). Five of the seven irrigated sites had N applied through irrigation > 12 kg N ha^{-1}, and this was included in determining the EONR of these sites. The EONR results were used as the standard for evaluating all other N recommendation tools. For 19 of the 49 sites, the at-planting and split EONR values were found statistically (P=0.05) to be same, within \$2.50 ha^{-1} of each other. Thus for these the EONR used was the average of the two timings. This approach was also consistent with previous separate analysis using this same dataset (Bandura, 2017).

Nitrogen Recommendation Tools Evaluated

Tools that were evaluated for improvement in this chapter included only those that were found successful from Chapter 2. These were defined as tools having an N recommendation that had a significant and positive linear relationship with EONR. The one exception was MRTN (explained below). This focus was given because analysis from chapter 3 showed tools which had a negative linear relationship with EONR did not improve with added soil and weather information, with the majority of algorithms tested in that chapter. Successful tools used from chapter 2 included the State-Specific yield goal (YG), three variations of the pre-plant soil nitrate test (PPNT), four variations of the pre-sidedress soil nitrate test (PSNT), and canopy reflectance sensing using the Holland and Schepers algorithm. In addition to these tools, MRTN was also evaluated for improvement with added soil and weather information because many of the successful tools utilize MRTN as its base N recommendation, and it is a tool that is currently promoted through many Midwest land-grant universities.

State-Specific Yield Goal

The State-Specific YG tool was evaluated to where sites within each state only used their respective state's YG method. All states except Wisconsin (WI) at one point in time utilized a YG, as such all but the WI sites are included in the State-Specific YG analysis (n =43). All YG methods followed a similar mass balance approach established by Stanford (1973), but each has been uniquely modified by adjusting coefficients within the calculation and incorporating additional soil and management information. For example, the Nebraska YG was changed by incorporating PPNT values that have been either estimated or measured to a depth of 120 cm.

All YG tools required an expected yield. The expected yield for each site was determined using the average of the previous five-yr county corn yields for the respective county the site was within. The five-yr average was then adjusted based on the soil productivity of the predominantly mapped soil of each site, similar to that done by Laboski et al. (2012). This procedure classifies soil productivity as either low, medium, or high using soil texture, irrigation, depth to bedrock, drainage class, temperature regime, and available water content information. The yield of a site was then calculated by increasing the five-yr average yield for low, medium, and high soil productivity by 10, 20, or 30%, respectively. This estimated yield value was used to represent the YG for each method used to calculate the State-Specific YG (Table 1).

Soil Nitrogen Tests

Three distinct PPNT tools were evaluated. They are as follows: 1) General PPNT, 2) Minnesota (MN) PPNT, and 3) and WI PPNT (Table 1). Kitchen et al. (2017) detailed the sampling and NO_3–N analysis protocols for the PPNT tool. Two of the 49 sites did not complete PPNT sampling, so this tool was evaluated using 47 of the 49 sites.

Four PSNT tools were evaluated, including 1) General PSNT, 2) Iowa (IA) PSNT, 3) Indiana (IN) PSNT, and 4) WI PSNT (Table 1). These were tested under two different conditions. The first used a site average of measured NO_3–N from plots that received 0 kg N ha^{-1} at-planting. The second used a site average of measured NO_3–N from plots that received 45 kg N ha^{-1} at-planting. These are noted as PSNT 0 and PSNT 45, respectively, throughout this chapter. Soil samples were taken at the V5 ± 1 corn development stage and to a depth of 0.30 m.

MRTN

The MRTN recommendation values for all sites were determined by using values obtained in 2016, as only a few states had updated the MRTN database during the three years of this project. The MRTN values for IA, IL, IN, MN, and WI were obtained from the online Iowa State Extension N rate calculator (cnrc.agron.iastate.edu; verified 5 Mar. 2017). The MRTN values for North Dakota were obtained from the North Dakota Corn Nitrogen Calculator (www.ndsu.edu/pubweb/soils/corn; verified 5 Mar. 2017). The price of corn to N fertilizer ratio used was 10:1. Since neither Missouri nor Nebraska currently have the compiled database and online tool for an MRTN recommendation, sites from these states were excluded from this tool's evaluation, so the tool was tested at 36 sites.

Canopy Reflectance Sensing

Canopy Reflectance measurements were obtained using the RapidSCAN CS-45 (Holland Scientific, Lincoln NE, USA) the same day or just prior to the split N application. For the majority of sites, this was done at the ~V8-V10 corn development stage. Measurement details are described in Kitchen et al. (2017). The Holland and Schepers algorithm [HS; Holland and Schepers (2010)] was used to calculate an N fertilizer recommendation derived from these reflectance measurements. This algorithm is based on a sufficiency index calculated using measurements from both well-fertilized corn ("N-Rich") and minimally-fertilized corn that is referred to here as the "target" corn:

$$SI = \frac{VI_{Target}}{VI_{N-Rich}} \tag{1}$$

where SI is the sufficiency index; VI_{Target} is the vegetative index obtained from averaging measurements from all plots that received 45 kg N ha^{-1} at-planting and where a top-dress fertilizer was to be applied, and $VI_{N\text{-}Rich}$ is the vegetative index obtained by averaging all plots for two of the high N treatments (225 and 270 kg N ha^{-1} applied all at-planting). The NDRE vegetative index was calculated using the red-edge (730 nm; RE) and near-infrared (780 nm; NIR) wavelengths as shown:

$$NDRE = \frac{NIR-RE}{NIR+RE} \tag{2}$$

Fertilizer N recommendations were then calculated as described in Holland and Schepers (2010) as follows:

$$N_{Rec} = \left(MZ_i * N_{Opt} - N_{PreFert} - N_{CRD} + N_{Comp}\right) * \sqrt{\frac{(1-SI)}{\Delta SI}} \tag{3}$$

where N_{Rec} is the calculated N fertilizer recommendation; MZ_i is a scaling value ($0 \geq MZ_i \leq 2$) used to adjust the N recommendation based on areas of high or low yield performance; N_{Opt} was the base N rate, which is determined by the farmer; $N_{PreFert}$ is the amount of N already applied prior to sensing; N_{CRD} are N credits associated with the previous crop, NO_3–N in irrigation water, manure, or residual NO_3–N; N_{Comp} is an optional compensation factor for growth limiting conditions; SI is the sufficiency index, and ΔSI is a value to define the response range. For this analysis, MZ_i was left as the default value of 1.0, N_{opt} was set as the recorded farmer's N rate for each site, and $N_{PreFert}$ = 45 kg N ha^{-1}. With no supportive information relative to N_{CRD} and N_{Comp}, these two parameters were set to zero for all sites. The recommended value of 0.30 was used for ΔSI, which provides a response range between the measured vegetative index value between 0.70 and 1.00.

Incorporating Soil and Weather Information

To determine what soil and weather information was to be incorporated, an elastic net regression (Zou and Hastie, 2005) was used with soil and weather variables as the explanatory variables. The response variable of this regression was the difference between each tool's N recommendation and the EONR for each site as follows:

$$Tool_{Diff} = Tool_{N\,Rec} - EONR \qquad [4]$$

where EONR was calculated for both at-planting and split N application scenarios. The EONR values calculated at-planting were compared to MRTN, General PPNT, MN PPNT, and WI PPNT. The EONR values calculated from split N treatments were compared to MRTN, State-Specific YG, General PSNT 0 and 45, IA PSNT 0 and 45, IN PSNT 0 and 45, WI PSNT 0 and 45, and canopy reflectance sensing. Explanatory variables included measured physical and chemical soil properties and measured weather information. Soil properties were collected by sampling 120 cm-depth soil cores from each of the sites and analyzing by pedological soil horizon for texture, bulk density, pH salt, pH water, CEC, total N, total carbon, inorganic carbon, organic carbon, and organic matter as described in Table 2. Each of these soil properties was then depth weighted to obtain values for 0-30, 0-60, and 0-90 cm depth increments. Weather data were collected using on-site weather stations (HOBO U30 Automatic Weather Station; Onset Computer Corporation, Bourne, MA). Daily values were calculated for the maximum and minimum temperature and precipitation. These values were then used to calculate a cumulative precipitation, growing degree days, corn heat units, Shanon's diversity index of precipitation (evenness of rainfall), and abundantly and well-distributed rainfall as described by Tremblay et al. (2012), for two time periods, 30 days before planting up to the date of planting and from the date of planting to the time of sidedress (Table 2).

Many of these variables were highly correlated ($|r| > 0.85$). To minimize multicollinearity, the explanatory variables with the highest mean absolute pair-wise correlation values were removed from the model (Table 3). This procedure was automated by using the findCorrelation function from the R 'caret' package (Kuhn, 2017). Using the reduced number of variables, two models were created with and without two-way interaction terms for each N recommendation tool. All explanatory variables were normalized before running the model by subtracting the mean and dividing by the standard deviation. Preprocessing was necessary to minimize any bias the elastic net regression would have with variables that consisted of different units or ranges of values (e.g., cumulative precipitation vs. bulk density). The variables were converted back to their normal units to adjust N recommendation tools (explained in the next section).

The elastic net was fit with the 'caret' package using R Statistical Software (R Core Team, 2016). The elastic net was optimized by tuning the alpha and lambda parameters using a tenfold cross-validation repeated five times, where for each fold of the cross-validation the data were split randomly into ten folds. Nine of the folds were selected as a training dataset to fit a model for each combination of alpha and lambda tuning parameters, and the 10th fold was used as the testing dataset to calculate the accuracy of the predicted model. This was repeated a total of 50 times, and the accuracy for each combination of tuning parameters was determined using the average root-mean-square error (RMSE) across these 50 folds.

Statistical Analysis

For each model (with and without two-way interactions for each N recommendation tool), the out-of-sample RMSE was calculated for each cross-validation fold. These out-of-sample RMSE values were used to compare the accuracy of models developed with and without two-way interactions. A t-test was used to compare among each tool rthe difference between models with and without two-way interactions (α = 0.10).

Final models with all the essential variables and corresponding coefficients were used to adjust each N recommendation tool as follows:

$$Tool_{adj} = Tool - \text{Model P}arameters \qquad [4]$$

Each adjusted tool was then compared to EONR as described in Eq. 4 to determine if there was an improved performance of the tools at predicting EONR. This was accomplished by calculating 1) a coefficient of determination, 2) an RMSE for each adjusted tool using the difference between each tool's adjusted N recommendation and

EONR, and 3) the percentage of sites within ± 30 kg N ha^{-1} of EONR, or reasonably close to EONR (RC-EONR).

RESULTS AND DISCUSSION

The final models developed using the elastic net showed no significant difference between models with and without two-way interactions (α =0.10; Fig. 1). Only models developed with just the main effects are presented for the rest of this chapter.

Which Soil and Weather Variables Were Found to be Important?

The variables found to be important for explaining the difference between each N recommendation tool and EORN varied by the tool. Three of the fifteen tools (General PPNT, General PSNT 0, and WI PSNT 0) had final models where only the intercept was used to adjust these tools (Table 4). Eight of the fifteen tools' final models contained four or more variables. There was no apparent explanation as to why some N recommendation tools were best adjusted with the number of variables > 4 while others were ≤ 4. The most important factors for explaining the difference between N recommendation tools and EONR were the evenness of rainfall (SDI), soil pH (0-30 cm), and total carbon (0-90 cm). They were the most frequently used in the final model and on average had the highest absolute coefficient values (Table 4). To simplify the interpretation of these results, only the most important variables (SDI, pH, and total carbon) will be discussed in detail.

Weather Variables

The SDI was found to be an essential variable for adjusting the majority of N recommendation tools. This included both the measurements of SDI from 30 days before planting up to the date of planting (Planting) and from the date of planting to the date of sidedress (SD). The Planting and SD SDI were both found to be important for eight and nine of the fifteen N recommendation tools, respectively (Table 4). In all cases, the difference between each tool's N recommendation and EONR decreased with increasing SDI measurements. When used to adjust the N recommendation tool, the greater the SDI value, the greater the increase in an N recommendation.

Not surprisingly, SDI was determined as one of the most important variables as precipitation-based measurements often have a bigger impact on N fertilizer response and EONR calculations than soil parameters (Sogbedji et al., 2001; Tremblay et al., 2012; Sela et al., 2017). Precipitation is a major driving factor for soil organic matter mineralization, yield potential, NO_3–N leaching losses, and N uptake (Cassman and Munns, 1980; Schröder et al., 2000; Wilhelm and Wortmann, 2004; Melkonian et al., 2007). However, in this analysis, the cumulative precipitation was not found to be helpful in explaining EONR. The SD SDI helped explain 22% of the variation ($P < 0.001$) in the observed EONR values. This is similar to what Xie et al. (2013) reported, that SDI of precipitation and not precipitation alone better-explained corn response to sidedressed N fertilizer. This relationship could be explained by an increased N loss, decreased plant N uptake, or a reduced soil N supply. With increased SDI, the soil moisture would be maintained at a higher level over an extended period leading to possible soil surface runoff, N leaching, or denitrification (Maag and Vinther, 1996). Having consistent deficient soil moisture could also minimize root exploration leading to shallow rooting depths, thus limiting water availability and decreasing a plant's ability to take up N (Xie et al., 2013). Lastly, a laboratory experiment showed that mineralization decreases with increasing soil moisture above -200 kPa matric potential, thus limiting the N supply of the soil (Cassman and Munns, 1980). The general trend observed among the sites of this study showed the smallest SD SDI values were from the northwestern locations (North Dakota) and increased down to the southeast similar to the long-term rainfall trend seen in Fig. 2a. A more specific explanation of how SDI influenced the EONR for each location would require additional analysis, which is beyond the scope of this chapter.

In conjunction with the SD SDI, the Planting SDI was also found to be very influential. However, unlike the SD SDI, the Planting SDI's was not able to explain any variation of EONR (P = 0.92). This is not surprising as precipitation events 30 days prior to planting up to the date of planting would have a smaller impact on soil N and grain production compared to in-season precipitation events. As such, it is unclear how to agronomically explain how Planting SDI helped improve N recommendation tools used for a sidedress N application (usually occurring ~55 days after planting).

Soil Variables

Of all the soil parameters that were used in the final model, pH (0-30 cm) and total carbon (0-90 cm) were the most frequently identified as important (Table 4). The pH and total soil carbon across all sites ranged from 5.5 to 7.8 and 0.03 to 0.26 g C kg^{-1}, respectively. Both of these parameters increased as the difference between a tool's N recommendation and EONR increased. This translates into a more significant reduction to a tool's N recommendation with increasing pH or total carbon values (Table 5).

Soil pH affects soil fertility and drives many factors of the N cycle. For example, the microbial-driven conversion of ammonium to nitrate is optimized at pH values above 7.5 (Kyveryga et al., 2004). While denitrification rates are greatest at pH values less than 7 (Šimek and Cooper, 2002). The pH of a field was also found to commonly be related to corn yield and protein factors across multiple growing conditions and hybrids (Miao et al., 2006). However, directly relating pH to EONR showed no significant relationship ($P = 0.13$). For this investigation, the pH was found to be greater for the northern sites, where soils were formed under drier and colder conditions (Fig. 2b), and, therefore, are less weathered soils with free calcium carbonates. Adjusting for pH was necessary for many of the northern sites such, as North Dakota and Wisconsin, where pH > 7.0 (Fig. 3a). A few of these sites were non-responsive to added N fertilizer, suggesting the possible positive impact these pH values had on N mineralization when adequate organic matter was present. However, it is unlikely there is a direct causal relationship between EONR and mineralization, as the weather most likely drove the majority of N mineralization. This was observed as the 2016 ND sites were both non-responsive to added N fertilizer. However, the ND sites in 2014 and 2015, conducted on the same or nearby fields with very similar soil pH, had EONR values that ranged between 100 and 180 kg N ha^{-1}.

Adjusting for total soil carbon (0-90 cm) was also helpful for improving nine of the fifteen N recommendation tools. The organic carbon made up the majority of the total carbon in the soil (mean overall sites of 88 %). Only a few sites (mostly from North

Dakota) had any inorganic carbon measured throughout the soil profile. In the process of reducing the number of parameters to model, the organic matter and organic carbon measurements were found to be highly correlated ($r > 0.96$). As such, the modeling procedures narrowed the results to only include the total carbon from 0 to 90 cm. The total carbon was found to account for 16 and 13% of the variability around the at-planting and split EONR, respectively. Higher soil organic carbon is related to higher potential N mineralization rates (Culman et al., 2013), which would help explain the lack of fertilizer N response for many of the northern locations. In colder climates and with shorter growing seasons these soils formed with greater organic matter than soils in warmer wetter regions, and thus a potentially greater soil N supply exists in these soils today (Fig. 2b). Accounting for mineralization indirectly through total carbon allows tools to incorporate N supplied by the soil. The inability for tools to account for N mineralization rates is one reason that they performed poorly, as shown in chapter 2.

Improving Performance of N Recommendation Tools

Incorporating soil and weather information into the N recommendation tools helped improve the tools. For all tools, the average difference between each tool's N recommendation and EONR all came closer to 0 (Fig. 4), and most RMSE values were decreased (mean overall tools of 78 vs. 67 for unadjusted vs. adjusted, respectively). Additionally, there were four tools (MRTN used at-planting, MRTN used for a split application, IN PSNT 0, and WI PSNT 45) that when unadjusted were not significant and positively related to EONR. After adjusting for soil and weather information, these four tools were significant and positively related to EONR.

When evaluating the improvement of these tools using other metrics, the tools varied in how well they were improved. The most critical metric for improvement was to have an increased linear relationship (r^2) with EONR (mean overall tools from 0.11 to 0.22 for unadjusted vs adjusted, respectively), followed by an increase in the percentage of sites RC-EONR (mean overall tools from 35 to 41% for unadjusted vs adjusted, respectively; Table 6). Tools were grouped into three categories of improvement ("good," "mediocre," and "no") based on two of the performance criteria. Tools were classified as "good" when there was an increase in $r^2 \geq 0.13$ and an increase in the percentage of sites RC-EONR (Fig. 5; Table 6). Tools were classified as "mediocre" when adjusted models had an increase in $r^2 > 0$ and ≤ 0.13 (Fig. 6). The remainder tools were classified as not being improved (Fig. 7).

Nitrogen Recommendation Tools with "Good" Improvements

Tools that exhibited "good" improvements included MRTN for both at-planting and split applications, WI PPNT, IA PSNT 0, IN PSNT 0, and canopy reflectance sensing (Fig. 5). The most notable improvement based on the adjusted tools improved linear relationship with EONR occurred with MRTN for both application times (r^2 increased 0.22 and 0.21 for at-planting and split, respectively; Table 6). When averaging across all sites, MRTN alone came close to EONR. However, because the tool was unable to account for sites that were less responsive to N or sites which required high N rates (i.e., sites with excessive N loss), there was no significant linear relationship with EONR. Using weather and soil information helped adjust for these extreme sites. Nitrogen recommendations for the MRTN where it overestimated EONR were decreased based on sites characterized by a higher pH and total carbon content, and a lower Planting AWDR or SD SDI. Whereas sites where MRTN underestimated EONR, the MRTN N rate recommendations were increased. Sites where the adjustment increased the MRTN recommendation had lower soil pH and total carbon content, and a higher Planting AWDR or SD SDI (Fig. 3; Table 5). After adjusting for soil and weather information, MRTN showed a greater range of N rates of 80 to 240 kg N ha^{-1} (Fig 5a & 5b).

The WI PPNT showed a similar pattern as MRTN in its adjustment. This is expected as the WI PPNT uses MRTN as its base N recommendation and is further adjusted based on measured soil NO_3–N. Compared to the adjusted MRTN, the adjusted WI PPNT resulted in a higher r^2 value (0.29; $P < 0.001$) but a decrease in the percentage of sites RC-EONR (Table 6; Fig. 5a vs. 5c). This result indicates that MRTN could be adjusted using precipitation and soil pH to about the same performance level as with adjusted PPNT measurements; since the adjusted MRTN adds no new sampling and lab costs, farmers could deploy it with less expense.

Of these tools, the best-adjusted tool was the IA PSNT 0, where the adjusted tool's r^2 was 0.39 (P <0.001), and the percentages of sites RC-EONR was 55% (Table 6). Unadjusted the IA PSNT 0 had an r^2 of 0.24 (P <0.001), the highest of all the tools. Unlike MRTN, the PSNT based tools were successful at identifying when some sites would be less responsive and thus were more successful without adjustment (Fig. 5d). With adjustment, the most improvement occurred with sites where the IA PSNT 0 underestimated EONR, resulting in an increase in the N recommendation. The majority of adjustments were a result of the SD SDI.

The unadjusted IN PSNT 0 tool overestimated EONR for the majority of sites with 61% of the recommendations at 225 kg N ha^{-1} (Fig. 5e). Incorporating soil and weather information reduced this tool's N recommendation for many of these sites. This resulted in 33% of the sites to be RC-EONR after adjustments and 14% of the sites to remain RC-EONR. However, this adjustment also caused 10% of the sites that were initially RC-EONR to be adjusted to where they no longer were RC-EONR (Fig. 5e; Table 6).

Adjusting the Holland and Schepers canopy reflectance sensing algorithm with soil and weather information helped to improve the predictability of EONR, from an r^2 of 0.13 (P = 0.01) up to 0.36 (P <0.001; Table 6). This method for determining an N recommendation is unique in that it quantifies the plant's color and biomass using specific reflectance wavelengths to estimate a plant's N status. The conclusion here is that soil and weather information provided an estimate of N that was lost, but that this loss was not evident in the reflectance properties of the crop at the time of sensing. The soil and weather adjustment resulted in a general increase in the recommendation overall EONR values. As such, sites with low EONR values without adjustment had an even greater over-recommendation after being adjusted (Fig. 5f). This adjustment made the adjusted canopy reflectance sensing less able to correctly recommend N for sites that were less responsive to N fertilizer.

Nitrogen Recommendation Tools with "Mediocre" Improvements

Tools that were grouped as only having "mediocre" improvement with adjustment included MN PPNT, State-Specific YG, General PSNT 45, IA PSNNT 45, IN PSNT 45, and WI PSNT 45 (Fig. 6). Similar to WI PPNT, the MN PPNT is based off MRTN. However, the MN PPNT does not account for a baseline of soil NO_3–N as does the WI PPNT; this resulted in many of the unadjusted recommendations to be decreased more than the WI PPNT (Table 1). This additional decrease in MRTN using the MN PPNT method resulted in a weaker adjustment with soil and weather information than the adjustments made to the WI PPNT or MRTN. Even though on average, the unadjusted MN PPNT called for applying only 14 kg N ha^{-1} more than the WI PPNT. This goes to show the inconsistency of adjusting MRTN based on soil NO_3–N. Using soil pH, total carbon, and SDI as previously described would help better adjust MRTN than starting with the MN PPNT method.

The State-Specific YG was one of the few tools where the use of soil and weather information decreased the N recommendations for 41 of 43 sites. Utilizing a yield goal approach often results in overestimating the amount of N required, one of the limitations of this method as farmers can often be over-optimistic (Vanotti and Bundy, 1994). Unique from other tool's adjustments, the State-Specific YG relied solely on SD SDI values to adjust the tool. Values ≥ 0.71 resulted in an increase in the N recommendation, but with 41 of the 43 sites having an SD SDI value ≤ 0.71 the majority of sites were reduced (Table 5; Fig. 6b).

Of note, all the PSNT with 45 kg N ha^{-1} applied at-planting (i.e., PSNT 45) were classified as having "mediocre" improvements. These mediocre adjustments could be attributed to an increase into the range of N recommendation rates when using the PSNT with 45 kg N ha^{-1} applied at-planting. Adding 45 kg N ha^{-1} at planting would be expected to increase the amount NO_3–N in the soil that would be measured using the PSNT test, with this sampling occurring about 35 days after fertilizer application. But that the effect of N addition varied across the environments of this study. For a few sites the soil NO_3–N with added N was equivalent to no fertilization. Potentially this was the result of leaching (coarse-textured soils) or denitrification (fine-textured soils) during those early weeks after planting. However, with about ~90% of sites, there was an increase in the soil NO_3–N, when fertilized, was compared to non-fertilized. Of these sites, eight sites had PSNT values ≥ 45 kg N ha^{-1} than the non-fertilized crop and resulted in N recommendations ≤ 115 kg N ha^{-1}. However, only three of these eight sites had EONR values ≤ 115 kg N ha^{-1}. The conclusion is that when N fertilizer is added at or near planting, greater variability can result with the PSNT soil NO_3–N values and thereby the N recommendation. Since this variability is not systematic, incorporating soil and weather with PSNT 45 was less helpful in explaining variation between the tool and EONR. The opposite was found with PSNT 0 (Fig. 5d-e & Fig. 7b-c vs. Fig. 6c-f).

Of the all PSNT 45 tools, the IA PSNT 45 showed the best improvement based on the coefficient of determination. However, the adjustment also resulted in a decrease in the percentage of sites RC-EONR (Table 6). This occurred as the majority of the N recommendations were increased which moved six sites, which were previously RC-EONR, further away from EONR (Fig. 6d).

Poor Improvements

Three tools showed no improvement; these included the General PPNT, General PSNT 0, and WI PSNT 0 (Fig. 7). For both the General PPNT and General PSNT 0 there were no soil or weather variables that were identified as helpful in adjusting these tools.

As such, the General PPNT and General PSNT 0's N recommendations were only adjusted using the intercept of the model to where they were increased by 40 and 4 kg N ha^{-1}, respectively. In contrast, the WI PSNT 0, was able to be adjusted using soil and weather information to where the intercept was slightly decreased and the slope increased (Fig. 7c). However, the coefficients used for adjusting the tools did not provide any improvement (Table 6).

Was this Improvement Enough?

Improvement using soil and weather information was observed for many tools but tested over this 8-state, 3-season dataset still did not match what others have reported for some N recommendation tools. Tested against EONR, the Pennsylvania PSNT was found to have an $r^2 = 0.48$ (Schmidt et al., 2009). Utilizing a dataset from New York, Sela et al. (2017) showed that the Adapt-N crop growth model had an $r^2 = 0.56$. While Scharf et al. (2006) and Schmidt et al. (2009) in two separate investigations showed that chlorophyll meter derived N recommendations resulted in a strong linear relationship with EONR with r^2 values that ranged between 0.53 to 0.76. Bean et al. (2018) showed slightly better results from improving the Missouri canopy reflectance sensing algorithm using soil and weather information and their interactions to obtain a relationship between the N recommendations and EONR with $r^2 = 0.43$. One of the likely reasons for the more mediocre results in this analysis is that the tools and their adjustments were tested using a dataset that represented a large range in weather conditions unlike what the previous studies had (Kitchen et al., 2017). Most of these tools tested were developed or tailored from field research within a given U.S. state. It is perhaps unreasonable to expect tools developed in specific states to perform well across a broad region. However, to do so shows whether existing tools are robust enough to fit a wide array of environmental extremes for growing corn. These results would suggest they are not. Additional improvements may be needed with different types, and intensity of information in order produce better performing corn N recommendations that could be used more universally.

CONCLUSIONS

Efforts to improve N recommendation tools utilizing soil and weather information was successful for the 12 of the 15 tools evaluated. Many of the improvements occurred at locations that overestimated EONR as any adjustment was based on soil information, while sites that underestimated EONR were improved with weather information. Tools overestimated EONR when they did not take into account the potential soil N supply of a site. Much of the N supply could be accounted for with total carbon and soil pH. Tools underestimated EONR when conditions lead to excessive N loss, accounting for this with an evenness of rainfall was shown to be a useful adjuster.

The best adjustments occurred with tools that prior to being adjusted were able to identify non-responsive sites. These tools included the IA PSNT 0 and the Holland and Schepers canopy reflectance sensing algorithm. After adjusting these tools with soil and weather information, they had the highest linear relationship with EONR. In addition to these two tools, MRTN was also improved significantly. In fact, the adjusted MRTN had the greatest improvement (r^2 values increased from 0.01 to 0.23). The MRTN also performed equal to or even better than many of the PPNT based tools that rely on MRTN as the base N recommendation. By adjusting the MRTN with soil and weather information farmers could bypass taking soil NO_3–N samples, assuming that using precipitation indices (SDI or AWDR) and soil pH would be cheaper and easier to acquire than PPNT samples.

With all of these adjustments, however, many of these tools still had a weak linear relationship with EONR ($r^2 \leq 0.39$). This means the majority of the variability in EONR was not captured with N recommendation tools. Additional improvements could occur by incorporating other soil, weather, or management variables not included in this analysis that might better delineate N response. However, even with all the information, one might collect up to the point of a sidedress application, it would only account for about 1/3 of the growing season. Therefore, N recommendations will only be useful as "predictions" or "forecasts" that can be used to estimate corn N needs for the rest of the growing season.

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Table 1. Methods associated with corn N recommendation tools included in this investigation. Tool descriptions include YG as yield goal, PPNT as pre-plant nitrate test, and PSNT 0 and PSNT 45 as the pre-sidedress nitrate test with 0 and 45 kg N ha^{-1} applied at-planting, respectively. Variables used in calculations are Pop as plant population, OM as organic matter, and CEC as cation exchange capacity.

Tools	Approach & Calculation	Reference
Iowa YG	Calculation using an expected yield and a soybean credit equal to the previous year yield up to 56 kg N ha^{-1}. *IA YG = 1.12† × [1.22 × YG] or 1.12† × [0.9 × YG] for fine-silty Hapludolls – up to 56 kg N ha^{-1} soybean credit*	Voss and Killorn, 1998
Illinois YG	Calculation using an expected yield and a soybean credit of 45 kg N ha^{-1}. $N_{rec} = 1.12^{\dagger} \times [1.2 \times YG - N_{credit}]$	Hoeft and Peck, 1999
Indiana YG	Calculation using an expected yield and a soybean credit of 34 kg N ha^{-1}. $N_{rec} = 1.12^{\dagger} \times [-27 + 1.36 \times YG - N_{credit}]$	Vitosh et al., 1995
Minnesota YG	Calculation using an expected yield, organic matter content, and soybean credit of 22 to 45 kg N ha^{-1}. Soils are grouped into either low or high organic matter content with 30 g OM kg^{-1} soil being the threshold *(Table 1 of publication)*.	Schmitt et al., 2002
Minnesota YG	Calculation using an expected yield, plant population, and N supplying power of the soil based on organic matter and cation exchange capacity, and a soybean credit of 34 kg N ha^{-1}. $N_{rec} = 1.12^{\dagger} \times [0.9 \times YG + 4 \times Pop - N_{OM\text{-}credit} - N_{credit}]$	Brown et al., 2004
Nebraska YG	Calculation using an expected yield, measured or estimated inorganic soil NO_3–$N_{(0–120\ cm)}$, measured or estimated N supplied from organic matter, and a soybean credit of 39 or 50 kg N ha^{-1}, for sandy and non-sandy soils, respectively. An estimated amount of N applied through irrigation is also credited. The N recommendation rate is adjusted for soil texture classification and time of N fertilizer application. $N_{rec} = 1.12^{\dagger} \times [35 + (1.2 \times YG) - (8 \times NO_3\text{–}N_{(0\text{–}120\ cm)}) - 0.14 \times YG \times OM - N_{Credit}] \times Time_{adj} \times Price_{adj}$	Shapiro et al., 2008
North Dakota YG	The calculation is the measured soil NO_3–$N_{(0–60\ cm)}$ concentration (converted to mass) subtracted from the ND YG calculation and using a soybean credit of 45 kg N ha^{-1}. $N_{rec} = 1.12^{\dagger} \times [1.2 \times YG - NO_3\text{–}N_{(0\text{–}60\ cm)} - N_{credit}]$	Franzen, 2010

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Table 1. (Continued).

Tools	Approach & Calculation	Reference
General PPNT	The calculation is the measured soil NO_3–$N_{(0–60\ cm)}$ concentration (converted to mass) subtracted from MRTN‡. $N_{rec} = 1.12^{†} \times [MRTN^{‡} – NO_3–N_{(0–60\ cm)}]$	Bundy et al., 1999
MN PPNT	The calculation is 60% of the measured soil NO_3–$N_{(0–60\ cm)}$ concentration (converted to mass) subtracted from MRTN‡. $N_{rec} = 1.12^{†} \times [MRTN^{‡} – (0.60 \times NO_3–N_{(0–60\ cm)})]$	Kaiser et al., 2016
WI PPNT	Calculation using the measured soil NO_3–N concentration (converted to mass) in the top 90 cm (sample taken down to 60 cm and last 30 cm is estimated) subtracted from MRTN‡. To account for background soil NO_3–N 56 kg N ha^{-1} is subtracted from the total profile NO_3–N value. $N_{rec} = 1.12^{†} \times [MRTN^{‡} – (\Sigma NO_3–N_{(0–90\ cm)} – 50)]$, *no adjustments made if the sum of* NO_3–*N is below 56 kg N* ha^{-1}.	Laboski et al., 2012
General PSNT	MRTN or YG recommendation is adjusted proportionally based on if soil NO_3–$N_{(0–30\ cm)}$ concentration is below 25 mg kg^{-1} and above 10 mg kg^{-1}. The full recommended rate is applied if the soil NO_3–$N_{(0–30\ cm)}$ concentration is below 10 mg kg^{-1} and no additional N is applied if above 25 mg kg^{-1}.	Fernández et al., 2009
IA PSNT	Calculated using measured soil NO_3–$N_{(0–30\ cm)}$ concentration and a critical limit of 25 mg kg^{-}. To determine the N recommendation when NO_3–$N_{(0–30\ cm)}$ is below the critical threshold, the difference between the critical threshold and the measured NO_3–$N_{(0–30\ cm)}$ concentration is multiplied by 8. The critical limit is reduced by 3 to 5 mg kg^{-1} when spring precipitation is 20% above normal amounts. $N_{rec} = 1.12^{†} \times [(25\ mg\ kg^{-1} – NO_3–N_{(0–30\ cm)}\ mg\ kg^{-1}) \times 8]$	Blackmer et al., 1997
IN PSNT	Calculation using yield goal and soil NO_3–$N_{(0–30\ cm)}$ concentration (*Table 2 of publication*).	Brouder and Mengel, 2003
WI PSNT	A soil N credit is calculated based on soil NO_3–$N_{(0–30\ cm)}$ concentration and the yield potential of the soil. No N application is recommended if the measured soil NO_3–$N_{(0–30\ cm)}$ concentration is above 21 mg kg^{-1}. No N credits are applied if the soil NO_3–$N_{(0–30\ cm)}$ concentration is below 10 mg kg^{-1}. (*Table 6.6 of publication*)	Laboski et al., 2012

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Table 1. (Continued).

Tools	Approach & Calculation	Reference
MRTN	Yield response of N response trials spanning multiple years. From each trial, the yield is modeled as a function of N fertilizer and the N recommendation is determined by adjusting the price of corn and N fertilizer. Multiple N recommendations are grouped by geographical locations or soil properties.	Sawyer et al., 2006
Canopy Reflectance Sensing	Nitrogen recommendations are based on reflectance wavelengths measured with proximal sensors.	Holland and Schepers, 2010

Table 2. Weather and soil variables used in the complete dataset with calculations, methods, and associated citations.

	Complete Dataset		
Variables	**Calculations and Sample Depths**	**Method**	**References**
Weather			
Precipitation (PPT)	Sum of daily rainfall, mm.	Tipping bucket[§]	(Tremblay et al., 2012)
Corn heat units (CHU)	Σ(Ymax + Ymin)/2; Ymax and Ymin are the daily maximum and minimum temperatures, ^{o}C.	Temperature sensor[§]	(Tremblay et al., 2012)
Growing degree day (GDD)	Σ((Ymax + Ymin)/2)-T_{base}; Ymax, Ymin, T_{base} are the daily maximum, minimum, and base temperatures, respectively. T_{base} = 10^{o}C.	Temperature sensor	(Tremblay et al., 2012)
Shanon diversity index (SDI)	[-Σpi ln(pi)]/ln(n); where pi = Rain/PPT (daily rainfall relative to total rainfall in a given time; n = total number of days.	Tipping bucket	(Tremblay et al., 2012)
Abundant and well-distributed rainfall (AWDR)	SDI × PPT	Tipping bucket	(Tremblay et al., 2012)
Soil			
Clay	0-30, 0-60, 0-90 cm	Pipette	Soil Survey Staff (2014) 3A1
Sand	0-30, 0-60, 0-90 cm	Pipette	Soil Survey Staff (2014) 3A1
Silt	0-30, 0-60, 0-90 cm	Pipette	Soil Survey Staff (2014) 3A1
Cation exchange capacity (CEC)	0-30, 0-60, 0-90 cm	Ammonium acetate	Soil Survey Staff (2014) 4B1a1a1a1a-b1
Total N (TN)	0-30, 0-60, 0-90 cm	Dry combustion	Soil Survey Staff (2014) 4H2a1
Total carbon (TC)	0-30, 0-60, 0-90 cm	Dry combustion	Soil Survey Staff (2014) 4H2a1

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Table 2. (Continued).

Parameter	Calculations and Sample Depths	Method	References
Total organic carbon (TOC)	0-30, 0-60, 0-90 cm	Dry combustion	Nelson and Sommers (1996)
Total inorganic carbon (TIC)	0-30, 0-60, 0-90 cm	Difference between Total C and total organic C	
Organic matter (OM)	0-30, 0-60, 0-90 cm	Loss-on-ignition	Soil Survey Staff (2014) 5A
pH (Salt)	0-30, 0-60, 0-90 cm	pH Meter	Soil Survey Staff (2014) 4C1a1a2
pH (Water)	0-30, 0-60, 0-90 cm	pH Meter	Soil Survey Staff (2014) 4C1a1a2
Bulk Density (BD)	0-30, 0-60, 0-90 cm	Core	Soil Survey Staff(2014) 3B6a

† Daily temperature and precipitation measured using HOBO weather stations instrumentation (Onset Computer Corporation, Bourne, MA).

Table 3. Variables inputs used in the elastic net algorithm modeling. Within the table, X indicates parameters used for modeling and blank indicates parameters that were removed due to multicollinearity issues. Dashes indicate not applicable.

Parameter	Planting Tools	Split Tools
Weather		
PPT (Planting)†		
PPT (SD)‡	–	X
Corn Heat Units (Planting)		
Corn Heat Units (SD)	–	X
GDD (Planting)	X	X
GDD (SD)	–	
SDI (Planting)	X	X
SDI (SD)	–	X
AWDR (Planting)	X	X
AWDR (SD)	–	
Soil		
Clay	X (0-90 cm)	X (0-90 cm)
Sand	X (0-90 cm)	
Silt		X (0-60 cm)
Cation exchange capacity		
Total N		
Total carbon (C)	X (0-90 cm)	X (0-90 cm)
Total organic C		
Total inorganic C	X (0-30 cm)	X (0-30 cm)
Organic matter	X (0-30 cm)	X (0-90 cm)
pH (Salt)		
pH (Water)	X (0-30 cm)	X (0-30 cm)
Bulk Density	X (0-30 cm)	X (0-30 cm)

† Planting indicates data used 30 days prior to planting up to the date of planting

‡SD indicates data used from the date of planting up to the date of sidedress

Table 4. Normalized coefficients of influential variables selected by elastic net regression models for adjusting N recommendation tools. Includes weather variables calculated from 30 days prior to planting up to the date of planting (Planting) and from the date of planting to the date of a sidedress N fertilizer application (SD). These include cumulative precipitation (PPT), corn heat units (CHU), Shannon diversity index of rainfall (SDI), and abundant and well-distributed rainfall (AWDR). Soil variables include texture, total carbon (TC), total inorganic carbon (TIC), organic matter (OM), pH, and bulk density (BD). Soil variables were taken in depth increments of 0-30, 0-60, or 0-90 cm. Variables that were not in the final model have no value. The direction of the relationship is shown by the + or – sign. The four most frequent and influential soil and weather variables are bolded. Nitrogen recommendation tools included the State-Specific yield goal (YG), pre-plant nitrate test (PPNT), pre-sidedress nitrate test (PSNT) with 0 and 45 kg N ha^{-1} applied at-planting, MRTN, and canopy reflectance sensing using the Holland and Schepers algorithm.

Tool	Intercept	Planting GDD	**Planting SDI**	Planting AWDR	SD PPT	**SD SDI**	TIC 30	OM 30	**pH 30**	BD 30	Silt 60	Clay 30	Sand 30	**TC 90**
				------ mm ------			------- g kg^{-1} -------			g cm^{-3}	------------ g kg^{-1} ------------			
Planting														
MRTN	+15.8†			–5.3	NA	NA			+26.1					
General PPNT	–40.3				**NA**	**NA**								
MN PPNT	–25.7				**NA**	**NA**								+11.9
WI PPNT	–4.8†	–1.5	–9.3	–0.1	NA	NA	+1.9		+7.1			–0.6	+8.5	+1.2
Sidedress														
MRTN	+19.2†					–10.4			+18.9					
State-Specific YG	+23.4					–17.9								
General PSNT 0	–4.2													
IA PSNT 0	–25.4†		–1.9			–9.6		+1.9	+7.3	–2.4	+4.2			+7.0
IN PSNT 0	+39.6	–6.5	–1.3		+1.3	–11.9		+6.1	+1.3	–0.3	+6.1			+3.8
WI PSNT 0	–4.6													
Gen PSNT 45	–44.1		–7.9			–7.4			+10.6					+5.3
IA PSNT 45	+33.5	+0.6	–5.0			–8.7			+8.3	–4.2	+2.8			+6.1
IN PSNT 45	+2.2		–0.2			–8.1			+3.4	–5.4				+1.3
WI PSNT 45	–38.5		–6.2	–4.4		–10.3			+14.4	+1.2	+2.5			+8.2
Canopy Reflectance	–49.5†		–5.9			–8.8	+2.1		+6.6	–7.1	+1.5	+9.8		+3.6
Number of times variable are used		3	**8**	3	1	**9**	2	2	**10**	6	5	2	1	**9**
Mean of absolute value		2.2	**4.2**	2.5	0.7	**9.3**	1.3	2.7	**9.5**	2.9	2.9	3.5	4.3	**4.8**

†Indicates that the sign of the intercept changes when data is normalized (scaled and centered). See Table 5 for non-normalized coefficients.

Table 5. Coefficients of weather and soil parameters used to adjust N recommendation tools.

Tool	Parameter Adjustments
Planting	
$MRTN_{adj}$ =	**MRTN** + 265.9 + 0.2 *Planting_AWDR* - 43.7 *pH30*
General $PPNT_{adj}$ =	**General PPNT** + 40.3
MN $PPNT_{adj}$ =	**MN PPNT** + 45.6 - 18.7 *TC90*
WI $PPNT_{adj}$ =	**WI PPNT** - 12.3 + 0.3 *Planting_GDD* + 34.3 *Planting_SDI* + 0.3 *Planting_AWDR* - 6.2 *TIC30* - 6.1 *pH30* + 0.01 *Clay90* - 0.4*Sand90* - 1.9 TC90
Split	
$MRTN_{adj}$=	**MRTN** + 90.7 + 162.9 *SD_SDI* - 31.6 *pH30*
State-Specific YG_{adj} =	**State-Specific YG** - 203.5 + 287.5 *SD_SDI*
General PSNT 0_{adj} =	**General PSNT 0** + 4.2
IA PSNT 0_{adj} =	**IA PSNT 0** - 5.2 + 22.7 *Planting_SDI* + 157.5 *SD_SDI* - 2.0 *OM30* - 12.1 *pH30* + 19.8 *BD30* - 0.2 *Silt60* - 11.2 *TC90*
IN PSNT 0_{adj} =	**IN PSNT 0** - 142.5 + 0.2 *Planting_GDD* + 14.8 *Planting_SDI* - 0.01 *SD_PPT* + 194.7 *SD_SDI* - 6.6 *OM30* - 2.1 *pH30* + 2.5*BD30* - 0.3 *Silt60* - 6.0 *TC90*
WI PSNT 0_{adj} =	**WI PSNT 0** - 4.6
General PSNT 45_{adj} =	**General PSNT 45** +38.7 +93.5 *Planting_SDI* + 121.5 *SD_SDI* - 17.5 *pH30* - 8.5 *TC90*
IA PSNT 45_{adj} =	**IA PSNT 45** - 26.0 - 0.02 *Planting_GDD* + 58.8 *Planting_SDI* + 142.0 *SD_SDI* - 13.7 *pH30* + 34.4 *BD30* - 0.2 *Silt60* - 9.7 *TC90*
IN PSNT 45_{adj} =	**IN PSNT 45** - 107.8 + 0.2 *Planting_SDI* + 132.3 *SD_SDI* - 5.7 *pH30* + 44.2 *BD30* - 2.1 *TC90*
WI PSNT 45_{adj} =	**WI PSNT 45** +75.5 + 73.0 *Planting_SDI* + 0.1 *Planting_AWDR* + 168.2 SD_*SDI* - 23.8 *pH30* - 9.4 *BD30* - 0.1 *Silt60* - 13.2 *TC90*
Canopy $Reflectance_{adj}$ =	**Canopy Reflectance** - 58.0 + 70.0 *Planting_SDI* + 144.9 *SD_SDI* - 20.9 *TIC30* - 10.9 *pH30* + 57.8 *BD30* - 0.1 *Silt60* - 0.8 *Clay90* - 5.8 *TC90*

Table 6. The performance of each N recommendation tool unadjusted and adjusted with soil and weather information as presented in Table 5. The precision and accuracy were evaluated using the coefficient of determination measured from a simple linear relationship between each tool and the economically optimal N rate (EONR), RMSE of the difference between a tool's N recommendation and EONR, and the percentage of sites with ±30 kg N ha^{-1} of EONR or "reasonably close to EONR" (RC-EONR). The number of sites (n) included in the evaluation differed for each tool based on the availability of information to test the tool. Tools include the State-Specific yield goal (YG), pre-plant nitrate test (PPNT), pre-sidedress nitrate test (PSNT) with 0 and 45 kg N ha^{-1} applied at-planting, MRTN, and canopy reflectance sensing using the Holland and Schepers algorithm.

		Unadjusted Tools				**Adjusted Tools**			
N Recommendation Tool	**n**	***P*-Value**	**r2**	**RMSE**	**RC-EONR**	***P*-Value**	**r^2**	**RMSE**	**RC-EONR**
				-kg N ha^{-1}-	--- % ---			-kg N ha^{-1}-	--- % ---
At-Planting									
MRTN	36	0.53	0.01	77	39	<0.01	0.23	63	50
General PPNT	47	<0.01	0.15	85	21	<0.01	0.15	75	30
MN PPNT	47	0.01	0.13	80	32	<0.01	0.20	73	40
WI PPNT	44	<0.01	0.16	71	34	<0.001	0.29	65	36
Sidedress									
MRTN	36	0.45	0.02	72	42	<0.01	0.23	58	47
State-Specific YG	43	0.04	0.10	74	37	<0.01	0.19	64	37
General PSNT 0	49	0.01	0.13	70	43	0.01	0.13	70	41
IA PSNT 0	49	<0.001	0.24	68	41	<0.001	0.39	56	55
IN PSNT 0	49	0.21	0.03	83	24	<0.01	0.20	65	47
WI PSNT 0	49	0.02	0.11	73	41	0.02	0.11	73	39
General PSNT 45	49	0.07	0.07	92	29	<0.01	0.15	74	43
IA PSNT 45	49	<0.01	0.14	79	47	<0.001	0.27	65	35
IN PSNT 45	49	0.01	0.12	75	41	<0.01	0.18	70	47
WI PSNT 45	49	0.13	0.05	90	35	<0.01	0.17	71	39
Canopy Reflectance	49	0.01	0.13	85	22	<0.001	0.36	58	35

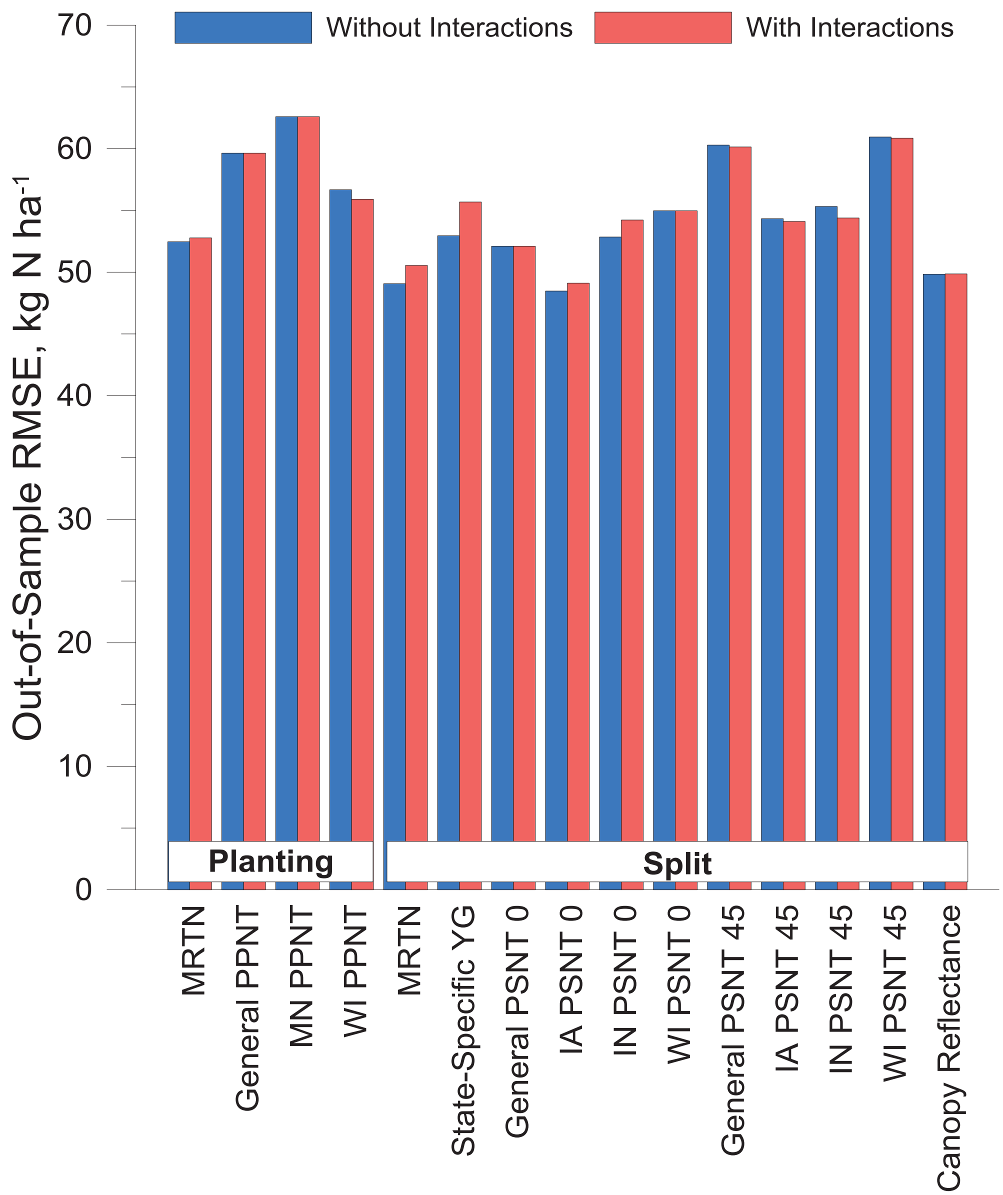

Fig. 1. The out-of-sample RMSE associated with models used to identify weather and soil information with and without two-way interactions for adjusting 15 N recommendation tools. No significant difference was observed between models with and without two-way interactions terms ($\alpha = 0.10$).

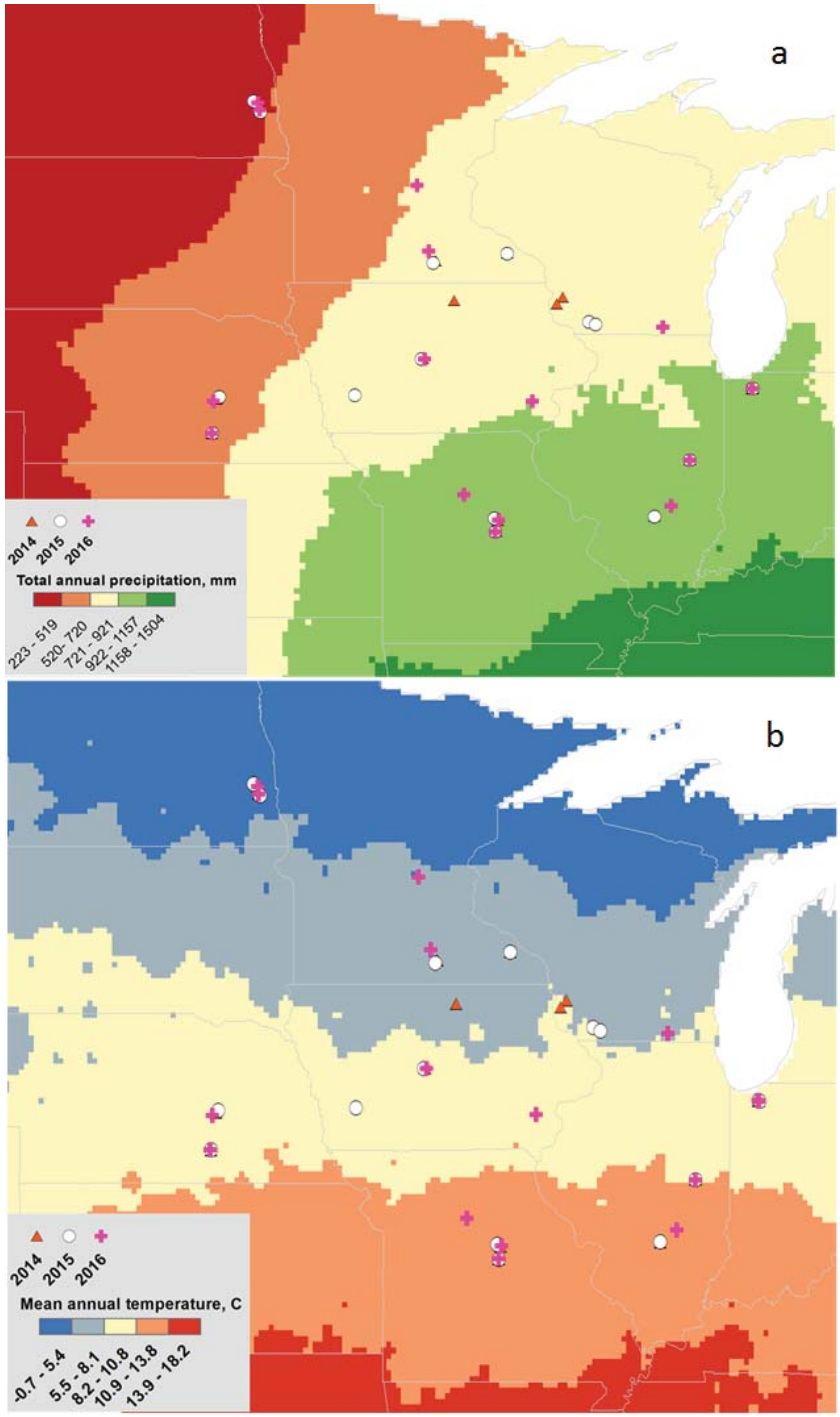

Fig. 2. U.S. maps depicting spatial distribution of a) mean annual rainfall from the National Severe Storms Lab (NOAA), and b) mean annual temperature. The location of the 49 study sites from 2014 to 2016 within the eight states Iowa, Illinois, Indiana, Minnesota, Missouri, Nebraska, North Dakota, and Wisconsin are also overlaid on each map. This figure was adapted from Kitchen et al. (2017).

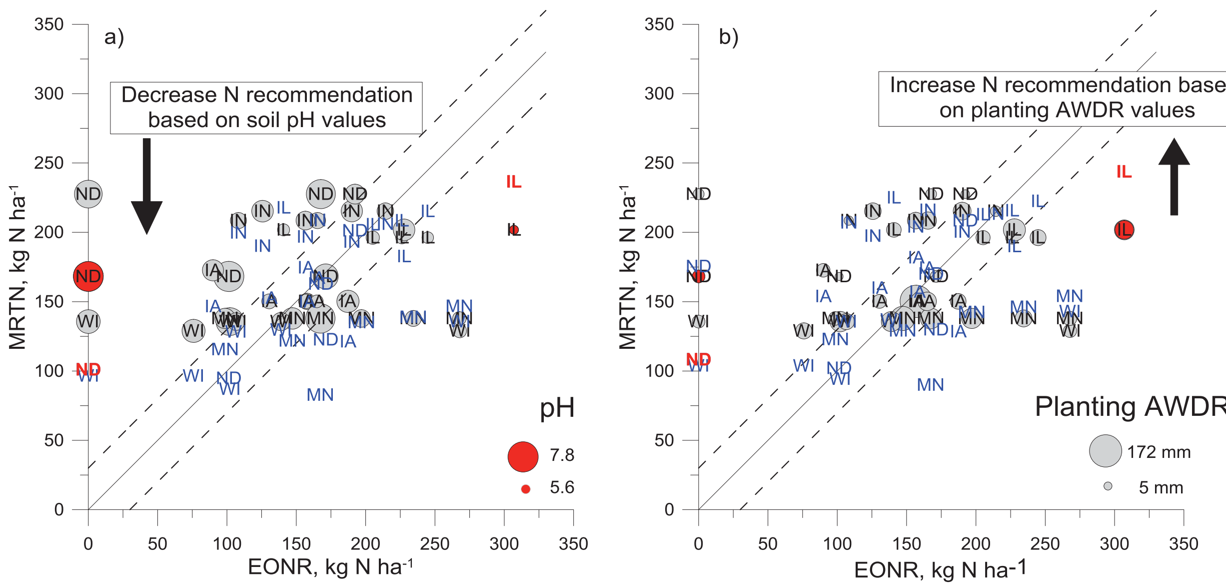

Fig. 3. MRTN N recommendation at-planting compared to the economically optimal N rate (EONR) before (sites as black labels) and after (sites as blue labels) adjusting with soil and weather information ($MRTN_{adj}$ = MRTN + 265.9 + 0.2 *Planting_AWDR* - 43.7 *pH*). The unadjusted N recommendations are displayed as bubbles with their corresponding abbreviated state label (black text), and the adjusted N recommendation using soil and weather information is shown with a similar abbreviated state label (blue text). Both graphs display the same data except the bubbles are sized differently based on either a) the soil pH (0-30 cm) or b) the abundantly and well-distributed rainfall (AWDR) calculated from 30 days prior to planting up to the date of planting. Two sites (IL and ND) are highlighted (red bubble for unadjusted and red abbreviated state label for adjusted) as examples of where soil pH effectively decreased N rate when the unadjusted tool overestimated EONR (ND), and where AWDR increased N rate based when the unadjusted tool underestimated EONR (IL). Solid 1:1 line is an indicator of a perfect predictor of EONR; the dashed lines indicated the area in which N recommendations were relatively close to EONR (or within ± 30 kg N ha^{-1} of EONR).

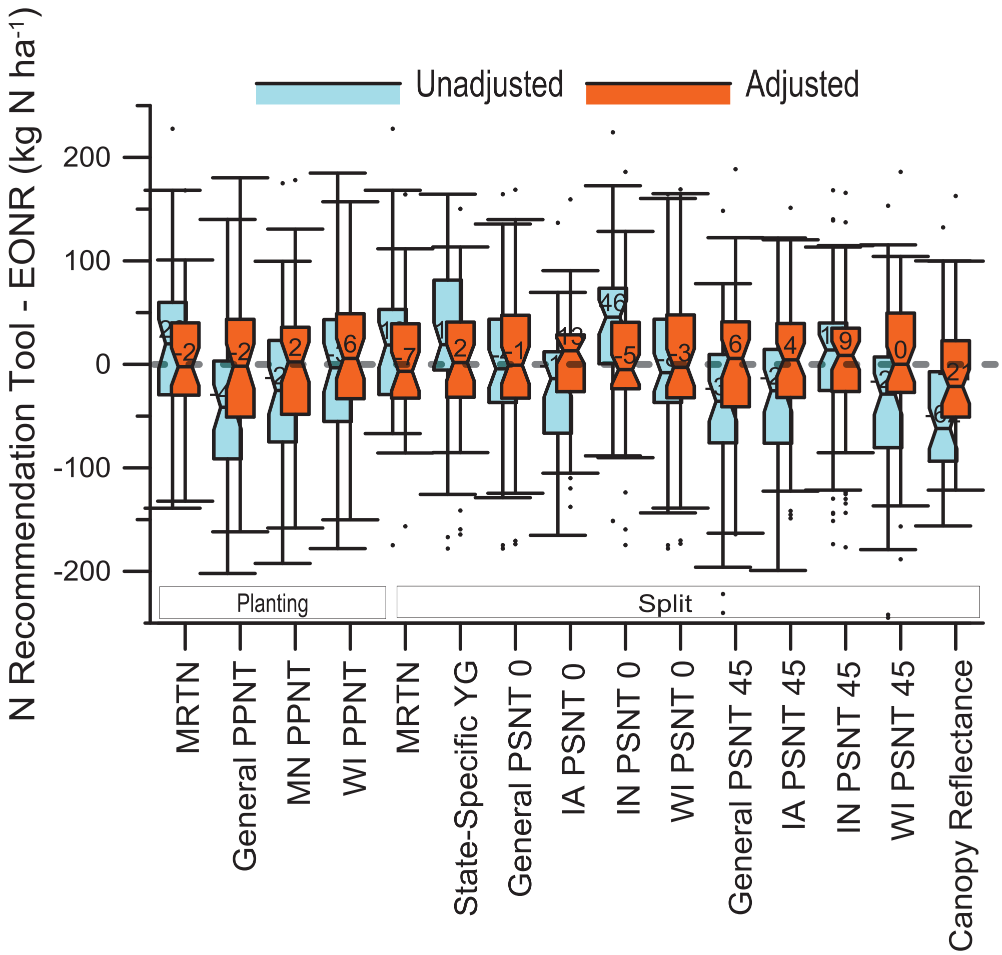

Fig. 4. Box and whisker plots showing the difference between each of the tools' N recommendation and the economically optimal N rate (EONR) for tools before and after adjusting with soil and weather information. The median is reported by the value in the middle of the box. Notches on the side of each the box indicate the 95% confidence interval around the median. Limits of the box indicate the first and third quartile, whiskers indicate 1.5 × IQR, and small circles indicate outliers. Improvement is assessed by the decrease in the box and whisker length, and the box is centered on the zero line (dashed line).

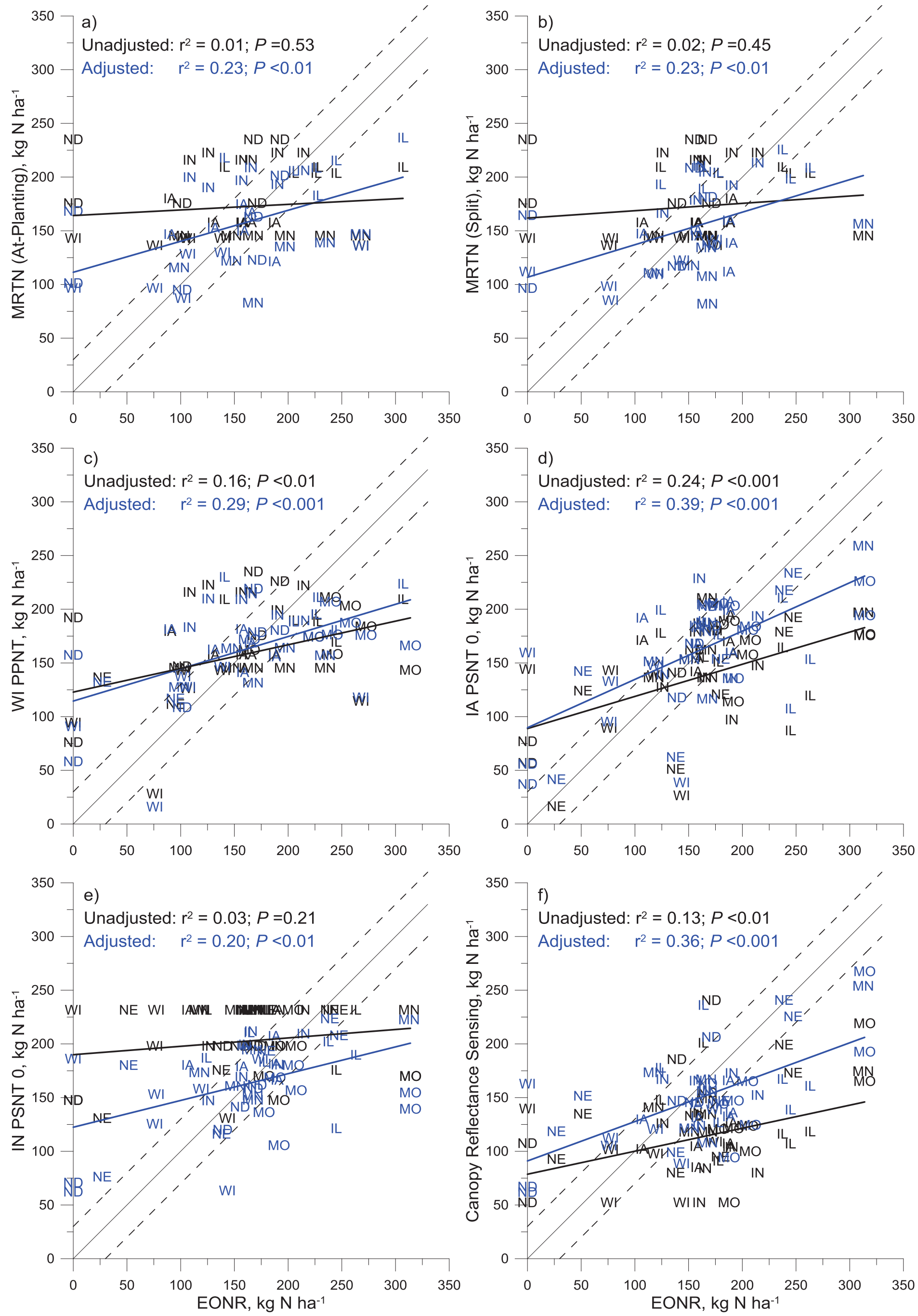

Fig. 5. Nitrogen recommendation tools that showed "good" improvement after being adjusted with soil and weather information. "Good" means tools had an increase in $r^2 \geq 0.13$ and an increase in the percentage of sites RC-EONR. Each tool's N recommendation was compared to the economically optimal N rate (EONR) before (black labels and line) and after (blue labels and line) adjusting with soil and weather information. Tools include a) MRTN used at-planting, b) IA pre-sidedress soil nitrate test (PSNT) with 0 kg N ha^{-1} applied at-planting, c) IN PSNT 0, d) General PSNT with 45 kg N ha^{-1} applied at-planting, and e) canopy reflectance sensing. The 1:1 line is an indicator of a perfect predictor of EONR, the dashed lines indicated the area in which tools ± 30 kg N ha^{-1} of EONR or relatively close to EONR.

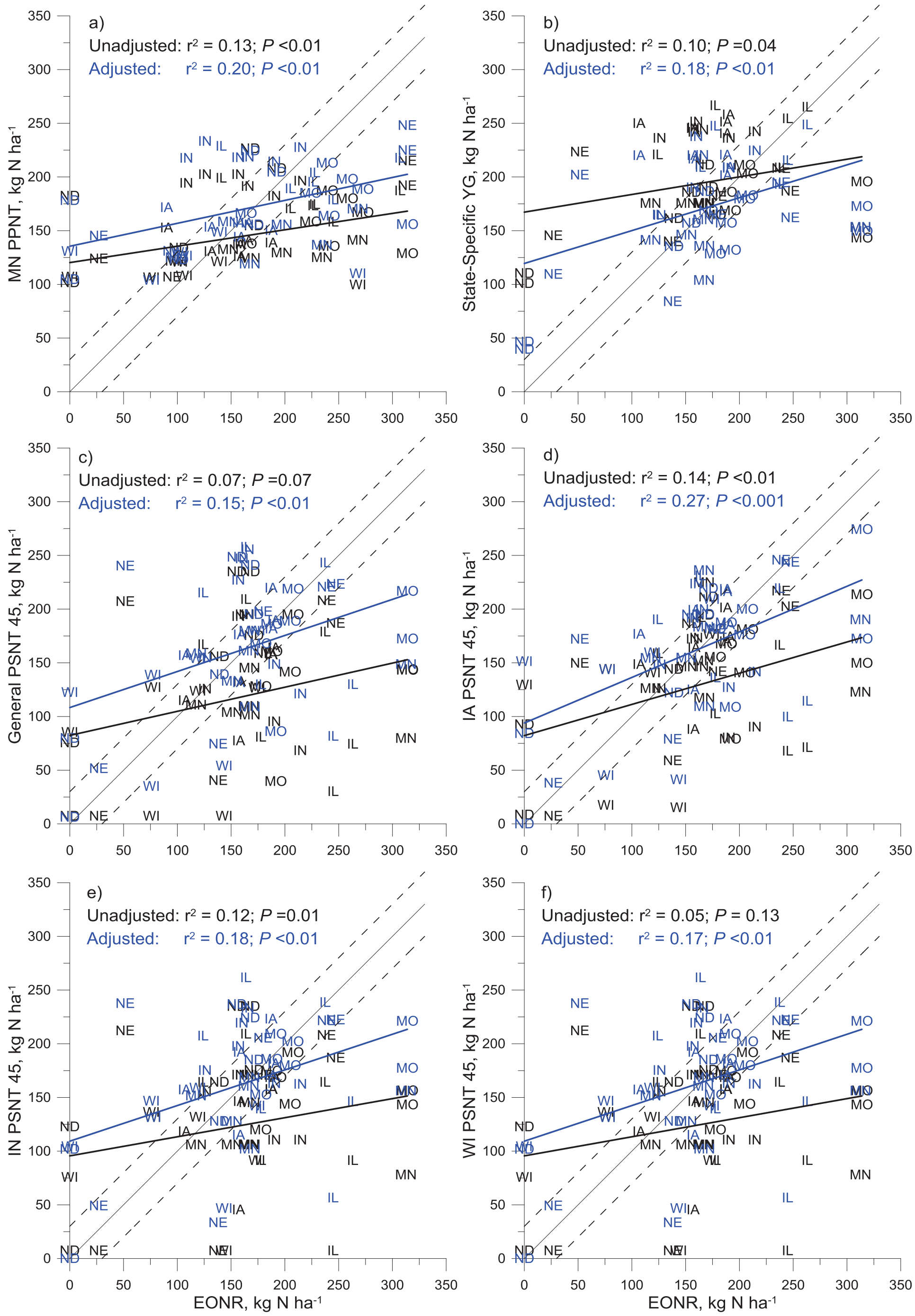

Fig. 6. Nitrogen recommendation tools that showed “mediocre” improvement after being adjusted with soil and weather information. “Mediocre” means that tools had an increase in $r^2 > 0$ and ≤ 0.13. Each tool’s N recommendation was compared to the economically optimal N rate (EONR) before (black labels and line) and after (blue labels and line) adjusting with soil and weather information. Tools include a) WI pre-plant soil nitrate test (PPNT), b) MRTN used for a split N application, c) IA pre-sidedress soil nitrate test (PSNT) with 45 kg N ha^{-1} applied at-planting, and d) WI PSNT 45. The 1:1 line is an indicator of a perfect predictor of EONR, the dashed lines indicated the area in which tools ± 30 kg N ha^{-1} of EONR or relatively close to EONR.

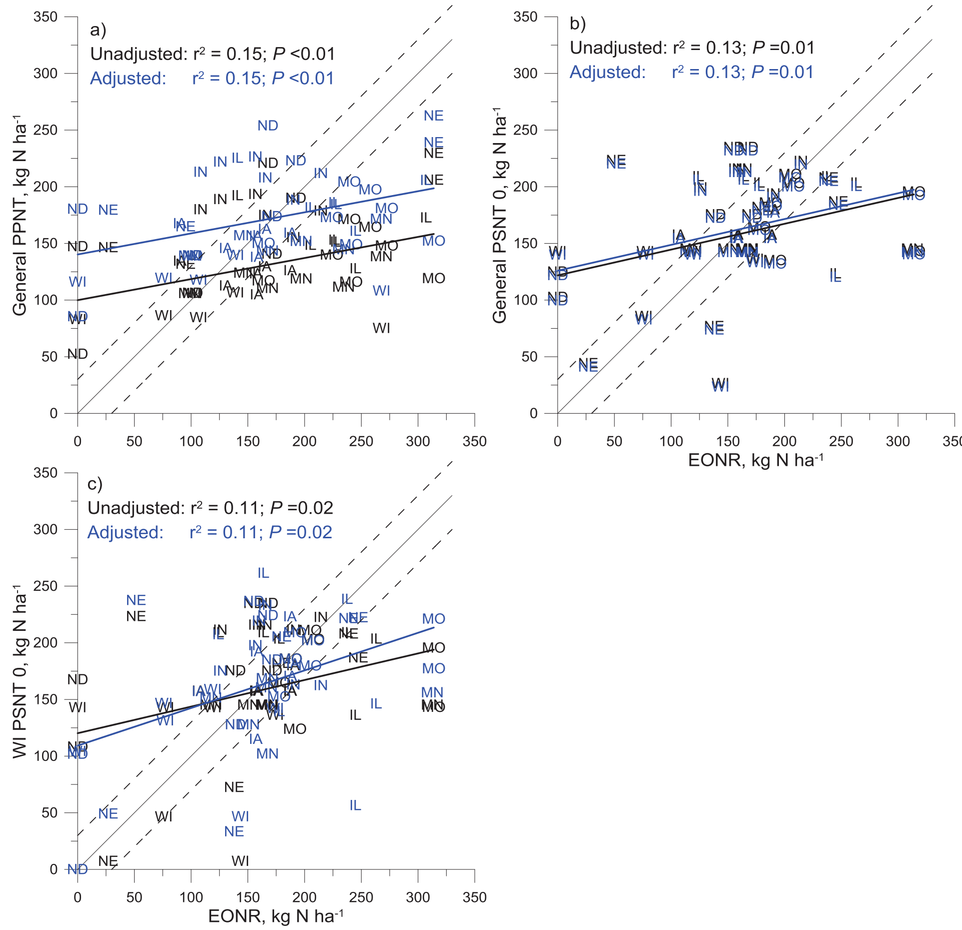

Fig. 7. The N recommendation tools that showed no improvements after being adjusted for soil and weather information. Each tool's N recommendation was compared to the economically optimal N rate (EONR) before (black labels and line) and after (blue labels and line) adjusting with soil and weather information. Tools include a) General pre-plant soil nitrate test (PPNT), b) General pre-sidedress soil nitrate with 0 kg N ha^{-1} applied at-planting (PSNT 0), and c) WI PSNT 0. The 1:1 line is an indicator of a perfect predictor of EONR, the dashed lines indicated the area in which tools ± 30 kg N ha^{-1} of EONR or relatively close to EONR.

Chapter 5: Tool Fusion of Corn Nitrogen Rate Recommendations for an Improved Prediction of Economically Optimal Nitrogen Rate

ABSTRACT

Improving corn (*Zea mays* L.) nitrogen (N) rate fertilizer recommendation tools can improve farmer's profits and help mitigate N pollution. Previous efforts to improve N recommendation tools showed moderate improvement when using soil and weather information, but still only accounted for 39% of the variability around the economically optimum N rate (EONR). Another possible way to improve N recommendation is to combine tools. This could be thought of as "tool fusion." The objective of this research was to improve N recommendations by combining N recommendation tools for both at-planting and split applied timings. The evaluation was conducted on 49 N response trials that spanned eight states and three growing seasons. An economical optimal N rate (EONR) was calculated for N treatments that were applied either all at-planting or split with 45 kg N ha^{-1} applied at-planting with the remaining fertilizer N applied at the V9 corn developmental stage. Models were developed using the elastic net and decision tree modeling approaches. For at-planting recommendation models, the EONR was regressed with the General yield goal, Wisconsin pre-plant soil nitrate test, and the Maize-N crop growth model as the explanatory variables. For a split applied N, EONR was regressed with the General yield goal, Wisconsin pre-sidedress soil nitrate test calculated with no N applied at planting, and canopy reflectance sensors using the Holland and Schepers algorithm as the explanatory variables. Regardless of the way tools were combined, using any combination of two or three N recommendation tools resulted in a decrease in RMSE

and an increase in the percentage of sites within 30 kg N ha^{-1}. However, not all combinations of two tools improved the linear relationship with EONR, but there was also no observed decrease in the performance. The best results for an at-planting recommendation occurred when the three at-planting N recommendation tools were combined with all interactions included in the elastic net regression model. This combined recommendation tool had a significant linear relationship with EONR (r^2 = 0.46; P <0.001), an increase of 0.27 over the best tool evaluated alone. The best combination of N recommendation tools for a split application occurred when using the three split tools with a decision tree (r^2 = 0.45; P <0.001), an increase of 0.18 over the best tool evaluated alone. This shows that this process of combining tools is a valid way to improve N recommendations to match EONR and thus could aid farmers in better managing N than using a single tool by itself.

INTRODUCTION

Over the last six decades, significant public resources have been spent on developing corn N rate recommendation tools (Nafziger et al., 2004; Morris et al., 2018). The goal for each of these tools has been to instruct farmers as to the optimal fertilizer N rate necessary for maximizing production and minimizing environmental degradation. However, developing an N recommendation system is very complicated due to spatial and temporal differences in crop N need as a result of genetics, management practices, and growing conditions (Scharf et al., 2005; Tremblay et al., 2012). A variety of N recommendation tools have been developed by focusing on different aspects of the soil-plant N dynamics. For example, soil samples used in-season allow for measurements of residual soil nitrate (NO_3–N) as well as an estimate of the N supplying capacity for that soil to determine if sufficient N is available in the soil. Canopy reflectance sensing is another unique tool that measures the soil-plant N dynamic indirectly by assessing the plant's biomass and color. A thorough review of many of these N recommendation tools can be found in Morris et al. (2018), and the strengths and weaknesses of some of the tools are summarized in Table 1.

Many of these publicly-available tools' performance has been assessed and been found not to be related to EONR, resulting in a mediocre performance across the U.S. Midwest (chapter 2). The effectiveness of these tools have been improved when soil and weather information was incorporated, but this only helps explain less than 40% of the variability of EONR (chapter 4; Bean et al., 2018). Improvements are still needed to maximize profits and minimize environmental damage associated with N loss to surface runoff, subsurface drainage, or to the atmosphere (Zhang et al., 2004; Hong et al., 2007;

Tremblay et al., 2012). Instead of spending additional time and resources developing new methods for determining corn N fertilizer rates, combining already developed methods might aid in improving the predictability of EONR. No one tool has been able to capture every aspect of the soil-plant N dynamic, with some being limited by soil or plant sampling constraints or fail to incorporate the spatial and temporal variability of weather and soil (Morris et al., 2018). Combing N recommendation tools together ("tool fusion") that vary in methodology will allow for an N recommendation to account for multiple aspects of the soil-plant N dynamic not previously accounted for in a single tool.

This tool fusion could be accomplished by following similar procedures used in other scientific fields for creating an ensemble of separate algorithms (Hansen and Salamon, 1990). An ensemble is merely the average of multiple predictive models, done to obtain one prediction, which is more accurate than the best predictive model used alone. There are multiple ways to create an ensemble which include: averaging predictions, taking a weighted average of predictions, or using other algorithms to determine which predictive models to include or exclude in the ensemble (Unger et al., 2009; Mendes-Moreira et al., 2012; Zheng et al., 2014). This strategy has been found useful in many fields of science. A few specific examples include the use of ensembles for crop, climate, and economic models to improve the predictability by using vastly different models developed by many different researchers (Rosenzweig et al., 2013; Wallach et al., 2016). This same theory could also apply toward improving N recommendation tools. The objective of this research was to determine if N recommendations could be improved by combining multiple N rate determining methods for both at-planting and split applied timings.

MATERIALS AND METHODS

Experimental Design

This research was conducted as a part of a public-private collaboration between DuPont Pioneer and eight U.S. Midwest universities (Iowa State University, University of Illinois Urbana-Champaign, University of Minnesota, University of Missouri, North Dakota State University, Purdue University, University of Nebraska-Lincoln, and University of Wisconsin-Madison). Each state conducted research on two sites each year during 2014 to 2016, with a third site in Missouri in 2016, totaling 49 site-years. About half the sites were on farmers' fields and the other half on University research stations. All states followed a similar protocol for plot research implementation including site selection, weather data collection, soil, and plant sample timing and collection methodology, N application timing, N source, and N rates, with specific details described in Kitchen et al. (2017). Treatments included N fertilizer rates between 0 and 315 kg N ha^{-1} applied either all at-planting or split where 45 kg N ha^{-1} was applied at-planting with the remaining fertilizer N applied at the V9 corn developmental stage.

Determining the Economic Optimal Nitrogen Rate

Grain yield in response to N fertilizer treatments was used to calculate the EONR on a site level as described in Kitchen et al. (2017), using proven quadratic or quadratic-plateau modeling methods (Cerrato and Blackmer, 1990; Scharf et al., 2005). Economically optimal N rate values were calculated for all N fertilizer applied at-planting, and N split applied between planting and a single top-dress application. The cost of N was \$0.88 kg N$^{-1,}$ and the price of corn was \$0.158 kg grain^{-1} (equivalent to

\$0.40 lbs N^{-1} and \$4.00 bu^{-1}). The EONR was set to not exceed the maximum N rate (315 kg N ha^{-1}). Five of the seven irrigated sites had N applied through irrigation > 12 kg N ha^{-1}, and this was included in determining the EONR of these sites. The EONR results were used as the standard for evaluating all other N recommendation tools and their improvement. For 19 of the 49 sites, the at-planting and split EONR values were found statistically (P=0.05) to be same, within \$2.50 ha^{-1} of each other. Thus for these the EONR used was the average of the two timings. This approach was also consistent with previous separate analysis using this same dataset (Bandura, 2017).

Nitrogen Recommendation Tools Considered for Combinations

General Yield Goal

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

WI PPNT

The General PPNT was calculated using soil NO_3–N samples taken to a depth of 90 cm. Kitchen et al. (2017) detailed the sampling and NO_3–N analysis protocols for the PPNT tool. The measured NO_3–N (converted to mass) is subtracted from N recommendations developed using the Maximum Return to N (MRTN). The MRTN recommendation values for all sites were determined by using values obtained in 2016, as only a few states had updated the MRTN database during the three years of this project. The MRTN values for IA, IL, IN, MN, and WI were obtained from the online Iowa State Extension N rate calculator (cnrc.agron.iastate.edu; verified 5 Mar. 2017). The MRTN values for North Dakota were obtained from the North Dakota Corn Nitrogen Calculator (www.ndsu.edu/pubweb/soils/corn; verified 5 Mar. 2017). The price of corn to N fertilizer ratio used was 10:1. Since neither Missouri nor Nebraska currently have a compiled database and online tool for an MRTN recommendation, sites from these states (n = 13) use their respective YG based recommendation (Brown et al., 2004; Shapiro et al., 2008). Both the Missouri and Nebraska substitute for MRTN are calculated as follows:

$$MO\ YG = 1.12 \times [0.9 \times YG + 4 \times Pop - N_{OM\text{-}credit} - N_{credit}] \quad [1]$$

$$NE\ YG = 1.12 \times [35 + (1.2 \times YG) - 0.14 \times YG \times OM - N_{Credit}] \times Price_{adj} \quad [2]$$

were YG is the expected yield calculated using the same protocol described in the General YG, Pop is the plant population, $N_{OM\text{-}credit}$ is a measure of the soil N supplying capacity based on organic matter and cation exchange capacity, N_{credit} is a soybean of either 34, 39, or 50 kg N ha^{-1} for Missouri, Nebraska sandy, or Nebraska non-sandy soils, respectively. The Nebraska yield goal utilized OM for organic matter and $Price_{adj}$ is the adjustment factor for the price of corn and N fertilizer. All calculations were done in English units and converted to SI by using a factor of 1.12.

Two of the 49 sites (2016 Nebraska sites) did not complete PPNT sampling, as such the PPNT was estimated from previous year's locations data. This was justified as one of the Nebraska sites was on the same research station as the 2014 and 2015 Nebraska sites. The other Nebraska site was conducted on a sandy soil, and minimal NO_3–N would be measured, similar to the 2014 and 2015 Nebraska sandy locations. The WI PPNT is not recommended for use in sandy soils, however, to maintain all observations, the four sandy locations were included in the WI PPNT, contrary to what was reported in chapter 2.

Maize-N

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

IA PSNT

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

Canopy Reflectance Sensing

Canopy Reflectance measurements were obtained using the RapidSCAN CS-45 (Holland Scientific, Lincoln NE, USA) the same day or just prior to the split N application. For the majority of sites, this was done at the ~V8-V10 corn development stage. Measurement details are described in Kitchen et al. (2017). The Holland and Schepers algorithm [HS; Holland and Schepers (2010)] was used to calculate an N fertilizer recommendation derived from these reflectance measurements. This algorithm is based on a sufficiency index calculated using measurements from both well-fertilized corn (“N-Rich”) and minimally-fertilized corn that is referred to here as the “target” corn:

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

where SI is the sufficiency index; VI_{Target} is the vegetative index obtained from averaging measurements from all plots that received 0 kg N ha^{-1} at-planting (which is different from previous chapters where results were reported based on plot that received 45 kg N ha^{-1} at planting), and $VI_{N\text{-}Rich}$ is the vegetative index obtained by averaging all plots for two of the high N treatments (225 and 270 kg N ha^{-1} applied all at-planting). The NDRE vegetative index was calculated using the red-edge (730 nm; RE) and near-infrared (780 nm; NIR) wavelengths as shown:

$$NDRE = \frac{NIR-RE}{NIR+RE} \quad [4]$$

Fertilizer N recommendations were then calculated as described in Holland and Schepers (2010) as follows:

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

where N_{Rec} is the calculated N fertilizer recommendation; MZ_i is a scaling value ($0 \geq MZ_i \leq 2$) used to adjust the N recommendation based on areas of high or low yield performance; N_{Opt} was the base N rate, which is determined by the farmer; $N_{PreFert}$ is the amount of N already applied prior to sensing; N_{CRD} are N credits associated with the previous crop, NO_3–N in irrigation water, manure, or residual NO_3–N; N_{Comp} is an optional compensation factor for growth limiting conditions; SI is the sufficiency index; and ΔSI is a value to define the response range. For this analysis, MZ_i was left as the default value of 1.0, N_{opt} was set as the recorded farmer's N rate for each site, and $N_{PreFert}$ = 45 kg N ha^{-1}. With no supportive information relative to N_{CRD} and N_{Comp}, these two parameters were set to zero for all sites. The recommended value of 0.30 was used for ΔSI, which provides a response range between the measured vegetative index value between 0.70 and 1.00.

Tool Fusion

Tool fusion was accomplished using either elastic net regression (Zou and Hastie, 2005) or decision tree regression models (Questier et al., 2005). For the elastic net based tool fusion, a series of ensemble models were created with tools used only for making an N recommendation at-planting (at-planting fused tool) and others for in-season N recommendations (split fused tool). Three N recommendation tools were selected for developing the at-planting and split fused tools. This analysis was limited to only three tools, to ensure that these methods would still be practical for a farmer to utilize without having to acquire excessive information. The at-planting fused tools were created using two and three tool combinations of the General yield goal (YG), Wisconsin pre-plant soil nitrate test (WI PPNT), and the Maize-N crop growth model. The split fusion tools were created using two and three tool combinations of the General YG, Iowa pre-sidedress soil nitrate test calculated with 0 kg N ha^{-1} applied at planting (IA PSNT 0), and canopy reflectance sensing based on the Holland and Schepers algorithm. Ideally, the best tool fusion would occur when N recommendation are diverse and accurate—similar to requirements for ensembling in machine learning (Hansen and Salamon, 1990). Following these guidelines, each of the tools was selected because their methods for determining an N rate had unique properties and inputs, with the majority of these tools also identified as some of the more accurate tools for predicting EONR as described in chapter 2.

The elastic net regression based fused tools were developed with the EONR regressed as a function of the N recommendation tools. For each at-planting and split fused tool, the N recommendation tools were evaluated under two scenarios. The first was with using only the main effects, and the second was using the main effects and all possible three-way and two-way interactions when applicable. For example, the at-planting fused tools without interaction terms included 1) General YG + WI PPNT, 2) General YG + Maize-N, 3) WI PPNT + Maize-N, 4) General YG + WI PPNT + Maize-N. Additional fused tools were created where the interaction terms were added to each of these ensembles. This process was repeated using the previously described three N recommendation tools selected for the split ensembles.

The elastic net used for tool fusion was fit with the 'caret' package using R Statistical Software (R Core Team, 2016; Kuhn, 2017). The elastic net was optimized by tuning the alpha and lambda parameters using a tenfold cross-validation repeated five times, where for each fold of the cross-validation the data were split randomly into ten folds. Nine of the folds were selected as a training dataset to fit a model, and the 10^{th} fold was used as the testing dataset to calculate the accuracy of the predicted model. The test statistic used to determine accuracy was the root-mean-square error (RMSE) between the predicted values and actual values of the 10^{th} fold. A total of 50 RMSE values were calculated for each combination of alpha and lambda values. The best combination of these tuning parameters was determined as the lowest average RMSE, which was then used to determine the coefficients necessary for creating each fused tool.

For both N application timings, a split decision tree modeling approach for tool fusion was also utilized. Regression tree models were created using the ‘caret’ and ‘rpart’ package in R (Therneau and Atkinson, 2018). The EONR was fit as a function of the three N recommendation tools for both at-planting and split. Each tree was developed where the variables were selected at each node of the tree to where the greatest homogeneity of the data would be explained (Questier et al., 2005). The homogeneity was measured as the absolute deviation from the mean.

Determining Tool Improvement

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

RESULTS AND DISCUSSION

Combining Nitrogen Recommendation Tools

The strengths of using the elastic net or decision tree based approaches for combing tools is that they can filter out any tools that do not improve the accuracy of the model. For three of the eight elastic net models, at least one N recommendation tool term (main or two-way interaction) in the model was not important. Of these three instances, the Maize-N tool was not considered important for two models, when modeling the WI PPNT and Maize-N with and without interactions (Table 2). The other instance was the exclusion of the two-way interaction between the General YG and IA PSNT 0 (Table 2). For these three elastic net models, there was minimal improvement (increase in $r^2 \leq 0.05$) when compared to the performance of the best tool evaluated alone (Table 3). This suggests that merely combining any two tools in an additive way will not improve all metrics of performance for N recommendations, but careful paring based on how the tools are interactively related to EONR may. For example, the WI PPNT on average came close to EONR and had a positive linear relationship with EONR (Fig. 2b), whereas, the Maize-N model greatly underestimated EONR but had no relationship with EONR (Fig. 2c). The combination of these tools had little improvement (Fig. 2f), but when the General YG, which greatly overestimated EONR, was combined with the Maize-N model there was a much greater improvement (Fig. 2e). Even though some pairs of tools did significantly improve the performance of predicting EONR, the combinations did cause the average difference between N recommendations and EONR to be close to 0 kg N ha^{-1} and a decrease in RMSE (Table 3). There was no observed performance loss by combining tools.

Performance of At-Planting Elastic Net Based Tool Fusion

The best improvement using the elastic net for at-planting tools occurred when all three N recommendations were combined and all three- and two-way interacting terms and the main effects were included in the model (r^2 =0.46 ; *P* <0.001). In comparison to previous methods for evaluating and improving N recommendation tools using this dataset (chapters 2 and 4), this was the best predictor of EONR. By incorporating soil and weather information, the best improvement only produced an r^2 = 0.29 (*P* <0.001) for at-planting tools (chapter 4). Here, the majority of combinations of tools used at-planting showed a similar or greater coefficient of determination (Table 3).

The best single combination of two tools was the Maize-N crop growth model and the General YG. When used alone the Maize-N underestimated EONR while the General YG overestimated EONR (Table 3; Fig. 2a & 2c). By themselves, the General YG and Maize-N model had only 14 and 18% of their sites RC-EONR, respectively. But these increased to 41% when combined. The Maize-N crop growth model was the only at-planting tool included in this analysis that was able to predict non-responsive sites (Fig. 2c). Incorporating the Maize-N model into ensembles with the General YG helped in reducing the N recommendations for those non-responsive sites, where the General YG greatly overestimated EONR. Accounting for these sites helped to improve the linear relationship between the elastic net based fused tool and EONR compared to tools evaluated alone.

Performance of Split Elastic Net Based Tool Fusion

Similarly to the at-planting elastic net models, the best improvement occurred when all three split N recommendation tools were combined by using all three- and two-way interaction terms and the main effects ($r^2 = 0.42$; $P < 0.001$). Compared to previous efforts of improving tools by incorporating soil and weather information, the best improvement was the IA PSNT 0 ($r^2 = 0.39$ $P < 0.001$; chapter 4). When adjusted with soil and weather information, the IA PSNT 0 resulted in 55% of sites RC-EONR. In contrast, the best-fused tool only had 47 % of sites RC-EONR. Hypothetically, an additional improvement to the fused tool might be obtained by adjusting the fused tool with soil and weather information, as was done in chapter 4.

Performance of Decision Tree Based Tool Fusion

The at-planting decision tree fused tool resulted in an $r^2 = 0.37$ ($P < 0.001$), which was not as good a performance as the best elastic net fused tool. However, this method did have the lowest RMSE and the highest percentage of sites RC-EONR (Table 3). A result of the decision tree method is that N recommendations are no longer a span of continuous rates. Instead, the decision tree bins the N recommendations based on the number of end nodes in the tree. In the case of the at-planting fused tool, this resulted in five different N rate recommendations (Fig. 5). For each N recommendation, many of the sites either under- or overestimating EONR, but the average came very close to EONR (Fig. 2l). For the at-planting decision tree fused tool, only two of the three N recommendation tools (General YG and WI PPNT) were used. The Maize-N model was not helpful in creating homogenous groups; as such, the modeling procedure did not include it. This corresponds with some of the elastic net models in which the Maize-N was also not selected in the final model (Table 2).

In contrast to the at-planting decision tree, the split decision tree fused tool resulted in an $r^2 = 0.45$ (P <0.001; Fig. 4l), which was the best performance of any split fused tool (Table 3). Also, this method had the lowest RMSE and the second highest percentage of sites RC-EONR (Table 3). This method used all three N recommendation tools in the model (Fig. 6). The downside to using this particular decision tree method is that interaction terms could not be used in the model, which was shown to be very helpful for many of the elastic net models.

Was this Improvement Enough?

The best improvement observed from this analysis (r^2 =0.46; P <0.001) was much better than the previous analysis used to adjust recommendations with soil and weather information ($r^2 = 0.39$; P <0.001; chapter 4). The best improvement observed with tool fusion was similar to what was reported for the relationship between the Pennsylvania PSNT and EONR ($r^2 = 0.48$; Schmidt et al., 2009). However, further improvement is necessary to match the performance reported for other N recommendation tools. Sela et al. (2017) showed that the Adapt-N crop growth model had an $r^2 = 0.56$. Scharf et al. (2006) and Schmidt et al. (2009) in two separate studies showed that chlorophyll meter derived N recommendations were more strongly related with EONR (r^2 between 0.53 to 0.76).

CONCLUSION

Efforts to improve N recommendations by combining two or three different N recommendations was successful and explained between 42 and 46% of the variability around EONR. The best improvements occurred when three tools were combined with all interaction terms. Nitrogen recommendations based on two or more tools showed an improvement that was much greater than the sum of the performance of each recommendation. An alternative way of combining N recommendations using a decision tree method was explored. Fused tools from this method were found to be as accurate as elastic net based fused tools. An example of which is the split decision tree where it explained 45% of the variability around EONR and had the lowest RMSE value of 53 kg N ha^{-1}. It also had one of the highest percentages of sites RC-EONR (45%).

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

Another feasible method for improving the elastic net and decision tree fused tools would be to adjust them using soil and weather information. A previous analysis showed that the evenness of rainfall between planting and the time of sidedress was able to explain 22% of the variation around EONR (chapter 4). Using this weather parameter could help to provide additional adjustments to the fused tools. It is not possible to explain all of the variability around EONR especially when recommendations are made early in the growing season without knowing if the following growing conditions would optimize or limit plant growth. However, the process of combining multiple tools provides an improved method of estimating EONR compared to using a single N recommendation tool.

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Table 1. Strengths and weaknesses of N fertilizer recommendation tools included in this investigation (YG, yield goal; PPNT, pre-plant nitrate test; PSNT, pre-sidedress nitrate test).

Tools	Pros	Cons	Citations
Yield Goal	Mass balance approach that is easily calculated. Nitrogen recommendations can be adjusted to account for soil N using credits (previous crop and residual soil NO_3–N measurements).	Poor relationships observed between YG calculations and EONR due to the uncertainty of final yields, management, previous crop effects, soil N supply, corn and fertilizer prices, and fertilizer use efficiency. Additionally, this method does not account for within-field variability due to soil and water properties.	Stanford, 1973; Lory and Scharf, 2003; Sawyer et al., 2006
PPNT	Soil NO_3–N levels can be assessed for residual N and N supplied by manure that could be available for plant use. Can be used as an adjustment to other N recommendations. Sampling can be taken during a lull in seasonal work.	Not a useful tool in more humid regions due to N loss during wet springs. Inaccurate test results due to varying weather affecting N mineralization rates. Additional cost and labor required. Requires deep sampling, down to 0.60 m or deeper.	Magdoff et al., 1984; Bundy and Andraski, 1995; Schröder et al., 2000; Lory and Scharf, 2003; Melkonian et al., 2007
PSNT	Has potential for better accounting of N loss from leaching or denitrification and N inputs from mineralization than PPNT. Successful at identifying N-sufficient sites.	Additional in-season sampling required and limited by wet conditions and short laboratory turn around. Limited by N loss due to temperature and rainfall immediately before and after sampling. Does not account for within-field spatial variability that results from variable soil and water interactions.	Magdoff et al., 1984; Fox et al., 1989; Magdoff, 1991; Andraski and Bundy, 2002

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Table 1. (Continued).

Tools	Pros	Cons	Citations
MRTN	Nitrogen response trials are used to determine N rates. Data are easily updated with additional experimental N-rate trials. Calculations reflect current economic status by including the price of fertilizer and corn. Provides a range that is within $1.00 that farmers can use depending on their risk level.	Does not address the issue of the year to year temperature or rainfall variability. Cannot predict site-specific N requirements and unlikely to accurately estimate EONR for each specific environment. Does not account for within-field spatial variability due to soil and water properties. Must estimate what the price of corn will be at the end of the season.	Nafziger et al., 2004; Sawyer et al., 2006; Melkonian et al., 2007
Crop Growth Models	Estimates possible weather scenarios during a growing season to minimize N loss and predict N supplied by the soil. Non-static N recommendation based on the genetic, environmental, and management conditions.	Initial inputs require time and money. Models may need to be calibrated to specific climate and soil conditions. Many parameters are estimated or generalized.	Setiyono et al., 2011; Sawyer, 2013; Morris et al., 2018
Canopy Reflectance Sensing	Nitrogen recommendations can be adjusted for plant response to soil and water variability within fields. Provides a real-time assessment of corn N status during the season. Various algorithms allow for adaptability for different conditions. Works well with high soil variability or in scenarios of uncertain N.	Expensive upfront costs for sensors and applicators. Needs a high-N area to normalize reflectance values. The sensor is not sensitive to within field changes in crop height. Hard to “see” slight N deficiency. Confounded by other plant stresses (e.g., sulfur). The amount of crop canopy closure affects readings, excessive soil exposure resulting in a diluted index value and a closed canopy results in saturated measurements.	Shanahan et al., 2008; Holland and Schepers, 2010; Kitchen et al., 2010; Franzen et al., 2016

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

Tool	Parameter Adjustments
Planting	
General YG + WI PPNT	188 - 0.58 **General YG** + 0.71 **WI PPNT**
General YG + Maize-N	438 - 1.5 **General YG** + 0.59 **Maize-N**
WI PPNT + Maize-N	61 + 0.67 **WI PPNT**
General YG + WI PPNT + Maize-N	305 - 1.19 **General YG** + 0.50 **WI PPNT** + 0.42 **Maize-N**
General YG:WI PPNT	1009 - 4.08 **General YG** - 4.36 **WI PPNT** + 0.02 **General YG x WI PPNT**
General YG:Maize-N	333 - 1.08 **General YG** + 1.84 **Maize-N** - 0.0048 **General YG x Maize-N**
WI PPNT:Maize-N	65 + 0.65 **WI PPNT**
General YG: WI PPNT:Maize-N	530 - 2.0 **General YG** - 1.25 **WI PPNT** + 0.87 **Maize-N** + 0.0065 **General YG x WI PPNT** - 0.0027 **General YG x Maize-N** + 0.0022 **WI PPNT x Maize-N -** 0.0000013 **MO YG x WI PPNT x Maize-N**
Split	
General YG + IA PSNT 0	171 - 0.36 **General YG** + 0.55 **IA PSNT 0**
General YG + Canopy Reflectance	193 - 0.32 **General YG** + 0.32 **Canopy Reflectance**
IA PSNT 0 + Canopy Reflectance	80 + 0.38 **IA PSNT 0** + 0.22 **Canopy Reflectance**
General YG + IA PSNT 0 + Canopy Reflectance	153 - 0.29 **General YG** + 0.35 **IA PSNT 0** + 0.19 **Canopy Reflectance**
General YG:IA PSNT 0	172 - 0.39 **General YG** + 0.59 **IA PSNT 0**
General YG:Canopy Reflectance	-194 + 1.24 **General YG** + 2.99 **Canopy Reflectance** - 0.01 **General YG x Canopy Reflectance**
IA PSNT 0:Canopy Reflectance	92 + 0.27 **IA PSNT 0** + 0.11 **Canopy Reflectance** + 0.00094 **IA PSNT 0 x Canopy Reflectance**
General YG:IA PSNT 0:Canopy Reflectance	0 + 1.9 **Gen. YG +** 0.96 **IA PSNT 0** + 3.79 **Canopy Reflectance** - 0.0005 **Gen. YG** x **IA PSNT 0** - 0.015 **General YG x Canopy Reflectance -** 2.53 **IA PSNT 0 x Canopy Reflectance** + 0.000003 **Gen. YG x IA PSNT 0 x Canopy Reflectance**

Table 3. Elastic net and decision tree fused tools used to predict the economically optimal N rate (EONR). The coefficient of determination calculated by regressing EONR as a function of each tool or fused tool N recommendation. The precision and accuracy of each N recommendation tool were evaluated using the average difference (N recommendation tool – EONR), RMSE of the difference between a tools' N recommendation and EONR, and the percentage of sites ±30 kg N ha^{-1} of EONR or "relatively close to EONR" (RC-EONR). The number of sites (n) included in the evaluation†. The number of tools (p) used in each regression or decision tree model. Tools include the General yield goal (YG), WI pre-plant nitrate test (PPNT), IA pre-sidedress nitrate test (PSNT) with 0 kg N ha^{-1} applied at-planting, Maize-N crop growth model, and canopy reflectance sensing using the Holland and Schepers algorithm. Dashes indicate not applicable.

		Main Effects Only					Main and Interaction Effects				
Tools	**n**	**p**	**r^2**	**Average**	**RMSE**	**RC-EONR**	**p**	**r^2**	**Average**	**RMSE**	**RC-EONR**
				----- kg N ha^{-1} ----		%			----- kg N ha^{-1} ----		%
At-Planting											
General YG	49	1	0.10	58	117	14	-	-	-	-	-
WI PPNT†	49	1	0.19	–7	76	35	-	-	-	-	-
Maize-N	49	1	0.00	–44	116	18	-	-	-	-	-
General YG + WI PPNT	49	2	0.29	0	68	35	3	0.37	0	64	33
General YG + Maize-N	49	2	0.33	0	67	41	3	0.37	0	64	41
WI PPNT + Maize-N	49	2	0.20	0	73	31	3	0.20	0	73	31
General YG + WI PPNT + Maize-N	49	3	0.39	0	64	41	7	0.46	0	60	41
Decision Tree (Fig. 5)	49	2	0.37	0	53	43	-	-	-	-	-
Split											
General YG	49	1	0.13	65	113	18	-	-	-	-	-
IA PSNT 0	49	1	0.24	–25	68	41	-	-	-	-	-
Canopy Reflectance‡	49	1	0.19	–23	73	29	-	-	-	-	-
General YG + IA PSNT 0	49	2	0.29	0	61	45	3	0.29	0	61	45
General YG + Canopy Reflectance	49	2	0.25	0	63	37	3	0.33	0	59	43
IA PSNT 0 + Canopy Reflectance	49	2	0.26	0	63	41	3	0.26	0	62	43
General YG + IA PSNT 0 + Canopy Reflectance	49	2	0.31	0	61	41	7	0.42	0	55	47
Decision Tree (Fig. 6)	49	3	0.45	0	53	45	-	-	-	-	-

†Values are different for WI PPNT than from chapter 2. Included sandy soil, contrary to the WI PPNT recommendations, and filled in two 2016 NE sites missing soil NO_3–N values with the average of the 2014 and 2015 data from nearby sites.

‡ Canopy reflectance sensing was calculated using plots that received 0 kg N ha^{-1} at-planting rather than what was used in previous chapters of 45 kg N ha^{-1} at-planting.

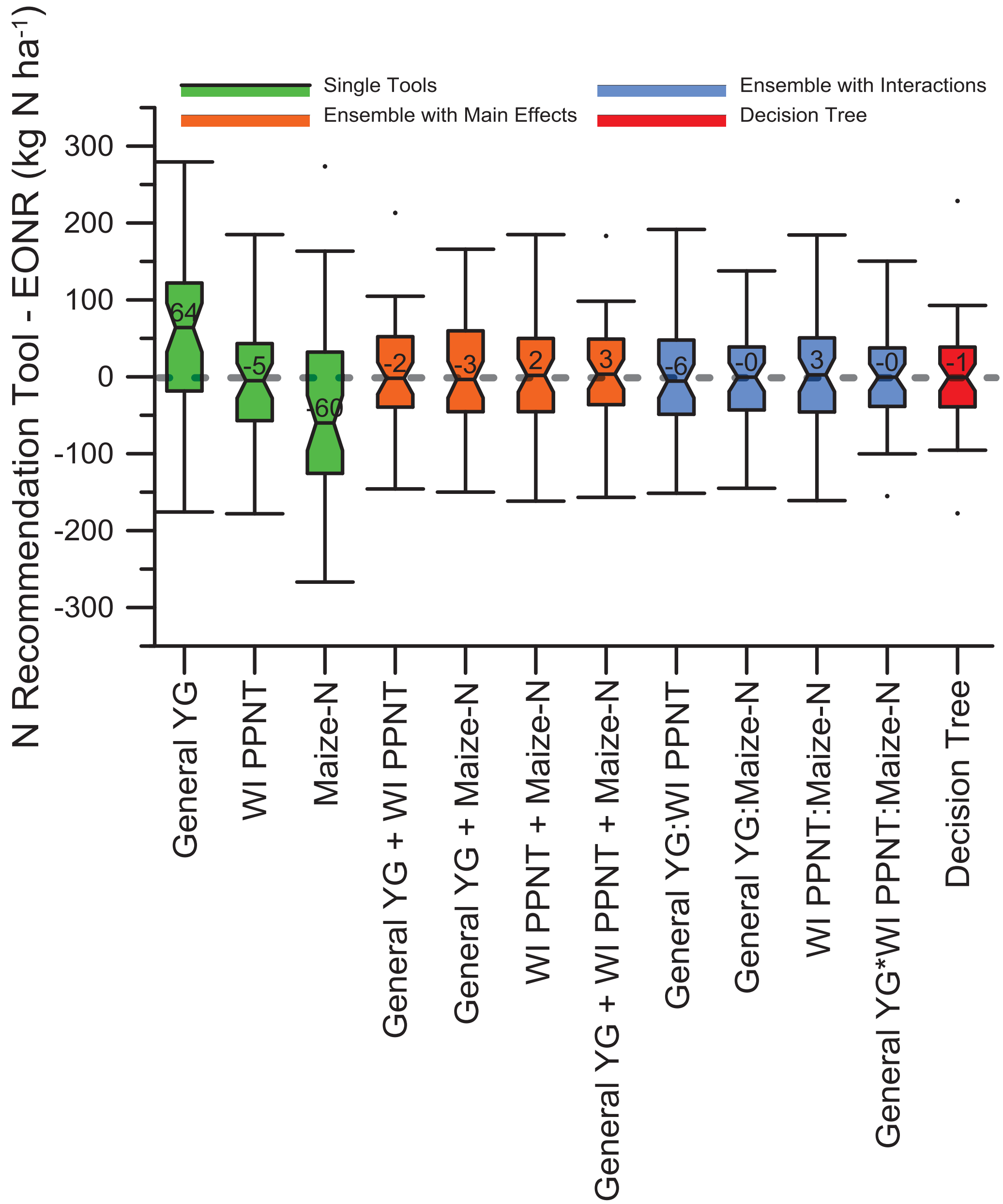

Fig. 1. Box and whisker plots showing the difference between the N recommendation tools used at-planting and the economically optimal N rate (EONR). General yield goal (YG), Wisconsin pre-plant soil nitrate test (WI PPNT), and the Maize-N crop growth model N recommendation tools were used to create eight combinations of elastic net models, four with and four without interaction terms and a decision tree. Models marked with ":" indicates fused tools developed with all combinations of main effects and interaction terms. The median is reported by the value in the middle of the box. Notches on the side of each box indicate the 95% confidence interval around the median. Limits of the box indicate the first and third quartile, whiskers indicate 1.5 × IQR, and small circles indicate outliers.

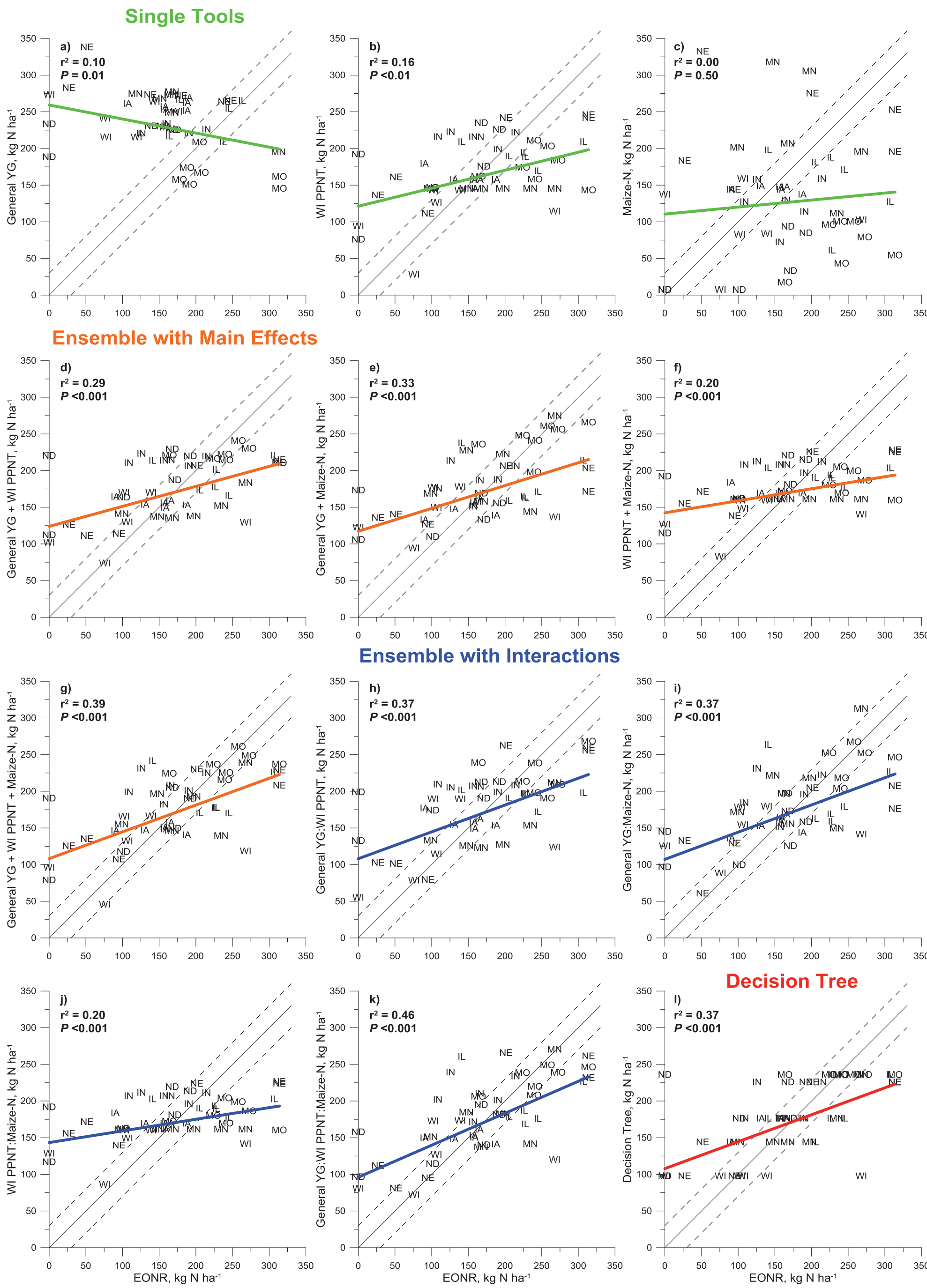

Fig. 2. At planting N recommendation tools evaluated relative to the economically optimal N rate (EONR). Tools included General yield goal (YG), Wisconsin pre-plant soil nitrate test (WI PPNT), and the Maize-N crop growth model. Graphs a-c) are tools evaluated alone (green), d-g) are combined using only main effects (orange), h-k) are combined using both main effects and interaction terms, and l) decision tree (red). Elastic net based fused N recommendation tools are marked with ":" indicates all combinations of main effects and interaction terms. The 1:1 line is an indicator of a perfect predictor of EONR, the dashed lines indicated the area in which tools ± 30 kg N ha^{-1} of EONR or relatively close to EONR.

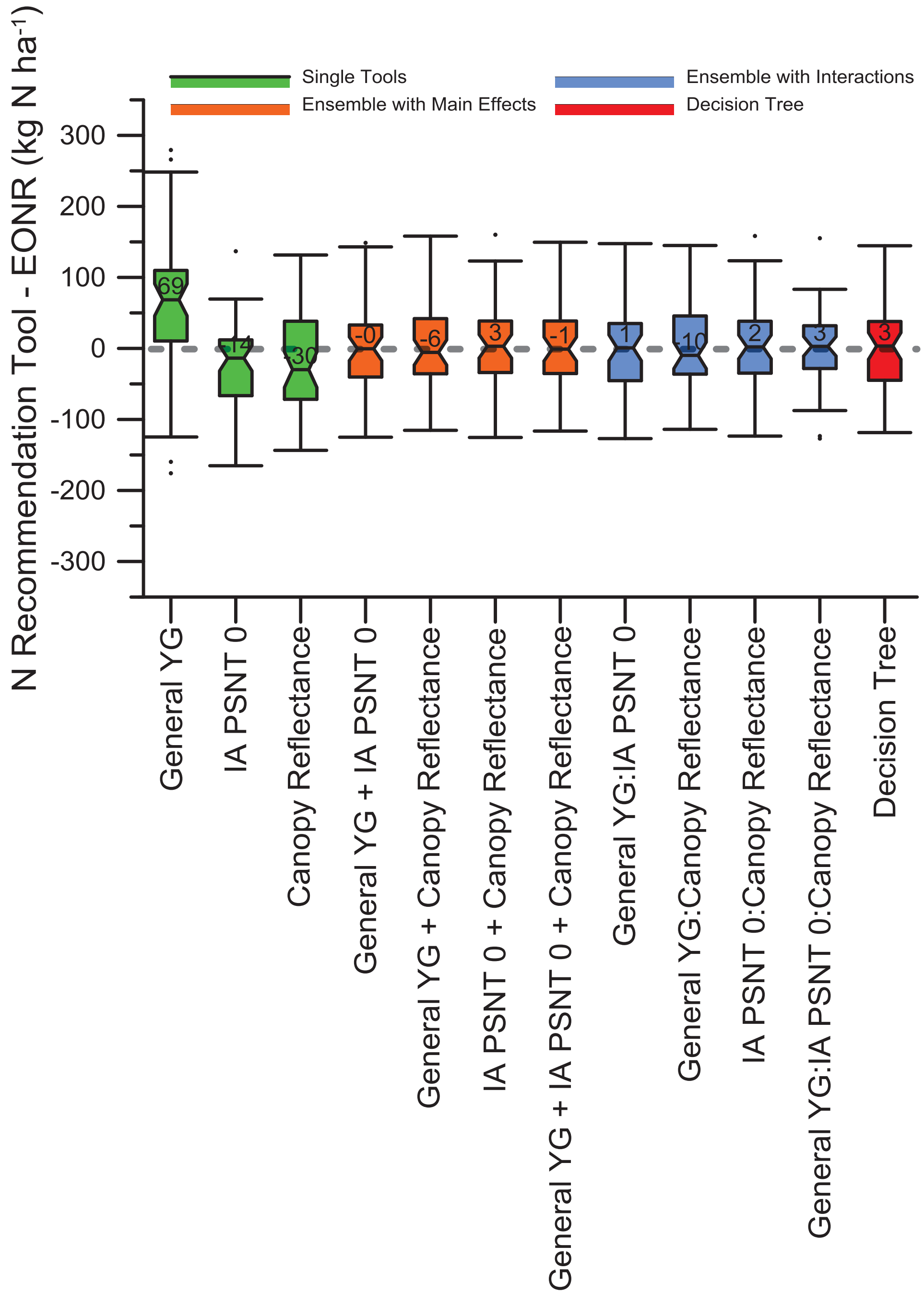

Fig. 3. Box and whisker plots showing the difference between the tools used at sidedress and the economically optimal N rate (EONR). General yield goal (YG), Iowa pre-sidedress soil nitrate test with 0 kg N ha^{-1} applied at-planting (IA PSNT 0), and canopy reflectance sensing N recommendation tools were used to create eight combinations of elastic net models, four with and four without interaction terms and a decision tree. Elastic net based fused N recommendation tools are marked with ":" indicates models with all combinations of main effects and interaction terms. The median is reported by the value in the middle of the box. Notches on the side of each box indicate the 95% confidence interval around the median. Limits of the box indicate the first and third quartile, whiskers indicate 1.5 × IQR, and small circles indicate outliers.

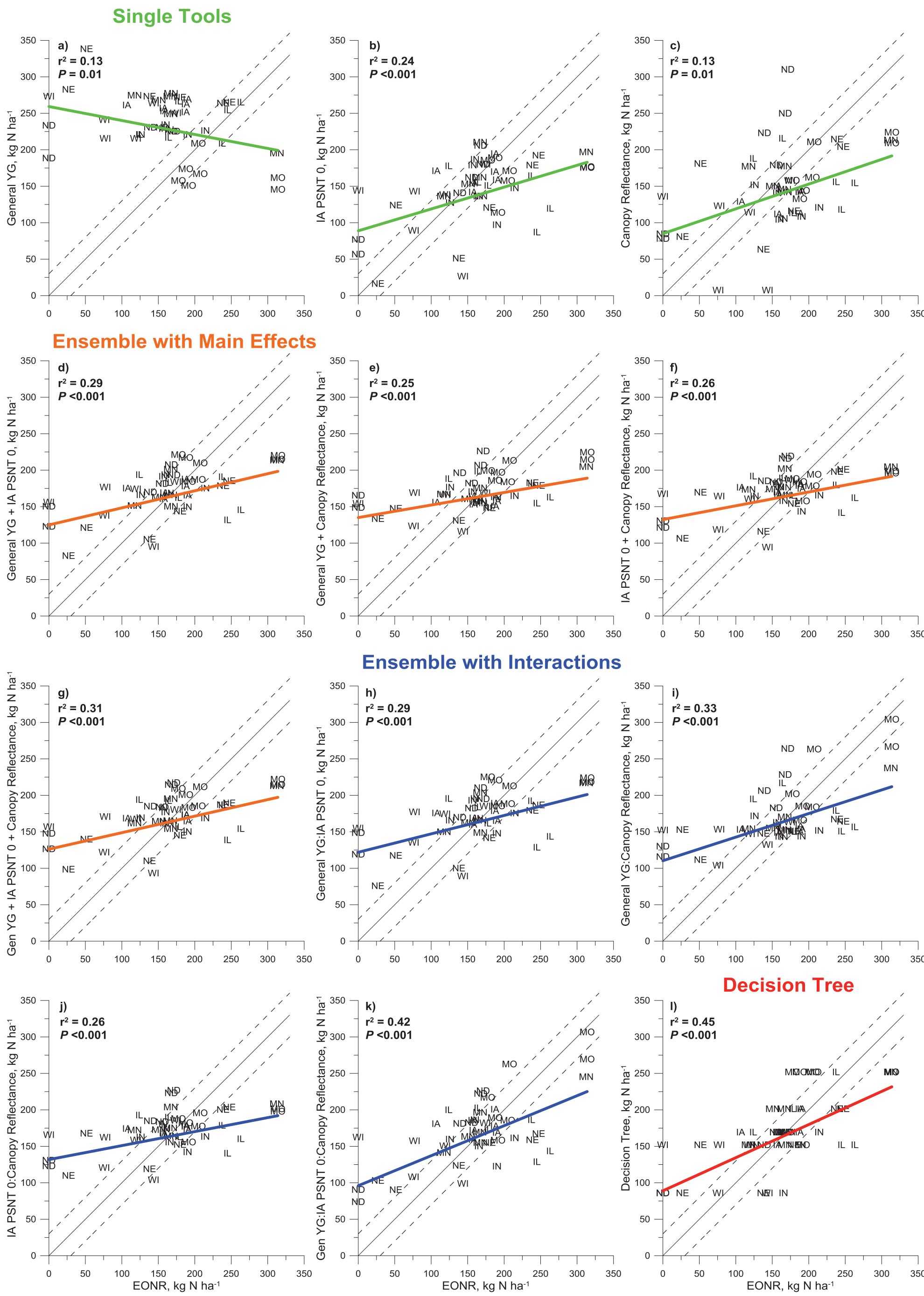

Fig. 4. Sidedress N recommendation tools evaluated relative to the economic optimal N rate (EONR). Tools included General yield goal (YG), Iowa pre-sidedress soil nitrate test with 0 kg N ha^{-1} applied at-planting (IA PSNT 0), and canopy reflectance sensing. Graphs a-c) are tools evaluated alone (green), d-g) are combined using only main effects (orange), h-k) are combined using both main effects and interaction terms, and l) decision tree (red). Elastic net based fused N recommendation tools are marked with ":" indicates all combinations of main effects and interaction terms. The 1:1 line is an indicator of a perfect predictor of EONR, the dashed lines indicated the area in which tools ± 30 kg N ha^{-1} of EONR or relatively close to EONR.

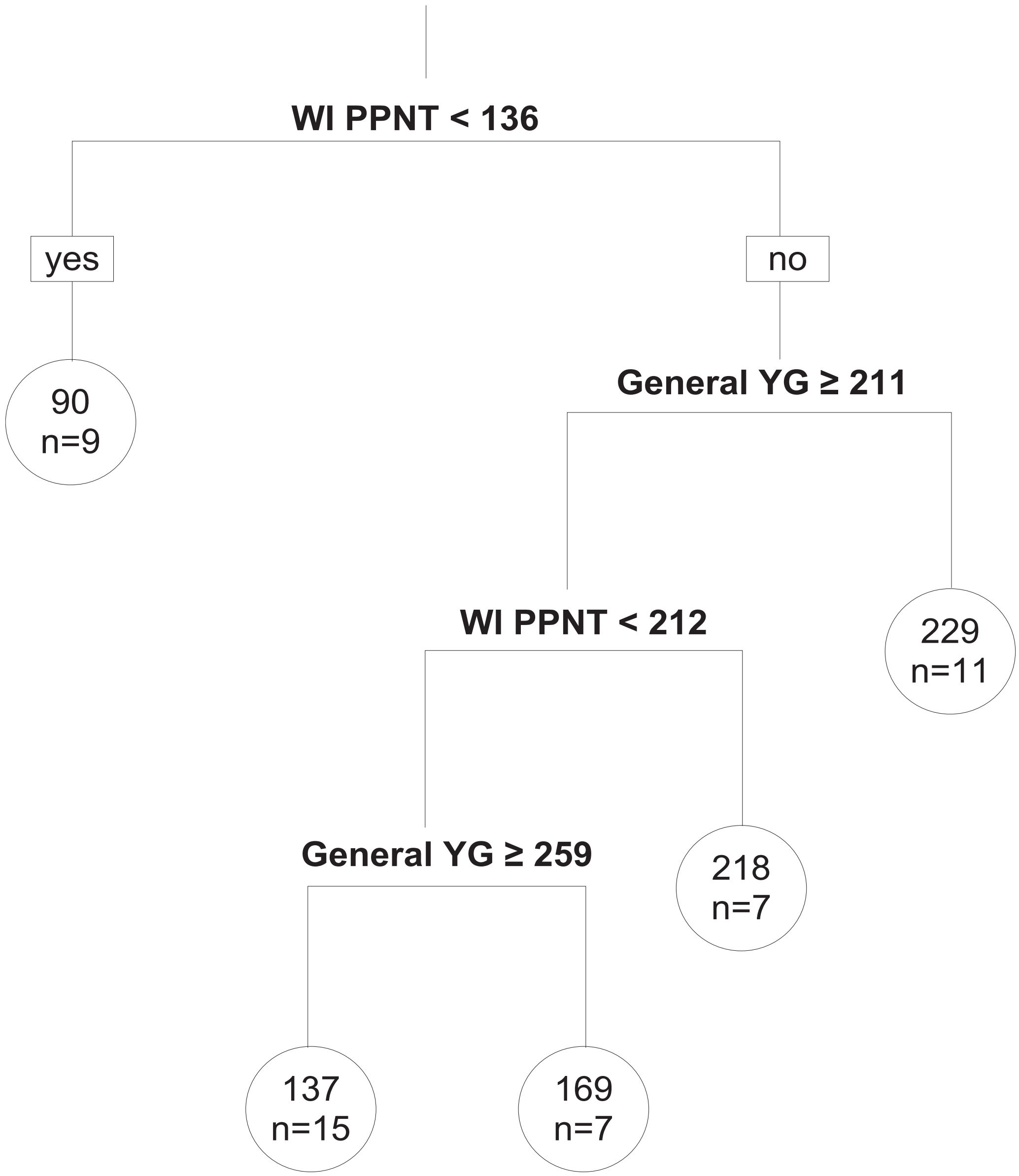

Fig. 5. The resulting decision tree model used to predict the economically optimal N rate (EONR) at-planting using the General yield goal (YG) and Wisconsin pre-plant soil nitrate test (WI PPNT). The number of sites (n) used to make up each terminal node of the tree.

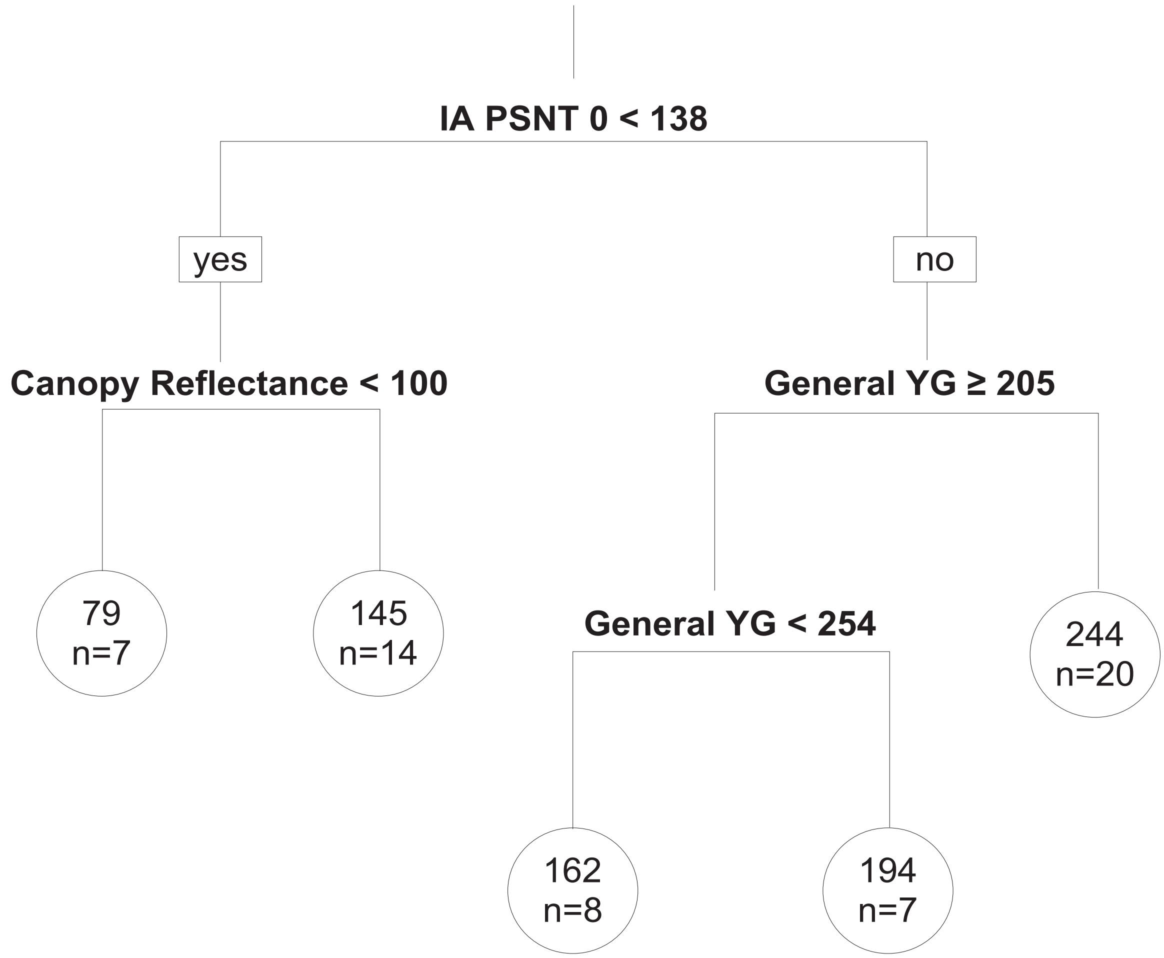

Fig. 6. The resulting decision tree model used to predict the economically optimal N rate (EONR) for an in-season N application using the General yield goal (YG), Iowa pre-sidedress soil nitrate test with 0 kg N ha^{-1} applied at-planting (IA PSNT 0), and canopy reflectance sensing using the Holland and Schepers algorithm. The number of sites (n) used to make up each terminal node of the tree.

Appendix A

Supplemental Material for Chapter 1

Table A1. Mean values for partial profit, environmental, and total cost of N recommendations tools relative to economically optimum N rates (EONR) for at-planting and split N applications across all sites. Tools include yield goal (YG), pre-plant nitrate test (PPNT), pre-sidedress nitrate test (PSNT) with 0 and 45 kg N ha^{-1} applied at-planting, MRTN, Maize-N crop growth model, and canopy reflectance sensing using the Holland and Schepers algorithm. Tools with a significant relationship with EONR (Table 3) are bolded. Dashes indicate not applicable.

	At-Planting			**Split**		
N Recommendation Tool	**Partial Profit**	**Environmental Cost**	**Total Cost**	**Partial Profit**	**Environmental Cost**	**Total Cost**
	--------Mean \$ ha^{-1} (Relative to EONR)--------			--------Mean \$ ha^{-1} (Relative to EONR)--------		
Farmer NR	–55	–40	–95	–51	–70	–121
General YG	–89	–119	–208	–87	–155	–241
IN YG	–96	–153	–249	–95	–193	–288
MN YG	–85	7	–79	–72	–17	–89
MO YG	–95	–135	–230	–87	–172	–259
NE YG	–91	13	–78	–98	25	–73
State-Specific YG[†]	–67	–36	–103	**–56**	**–61**	**–117**
General PPNT	**–102**	**55**	**–47**	-	-	-
MN PPNT	**–81**	**39**	**–42**	-	-	-
ND PPNT	–96	–20	–116	-	-	-
WI PPNT	**–61**	**9**	**–52**	-	-	-
MRTN	–50	–24	–74	–50	–48	–98
Maize-N	–201	32	–169	–196	12	–184
General PSNT 0	-	-	-	**–63**	**–8**	**–71**
IA PSNT 0	-	-	-	**–72**	**23**	**–49**
IN PSNT 0	-	-	-	–64	–85	–149
WI PSNT 0	-	-	-	**–69**	**–11**	**–80**
General PSNT 45	-	-	-	**–155**	**41**	**–114**

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Table A1 (Continued)

N Recommendation Tool	At-Planting			Split		
	Partial Profit	Environmental Cost	Total Cost	Partial Profit	Environmental Cost	Total Cost
	--------Mean $ ha^{-1} (Relative to EONR)--------			--------Mean $ ha^{-1} (Relative to EONR)--------		
IA PSNT 45	-	-	-	**–115**	**28**	**–87**
IN PSNT 45	-	-	-	**–78**	**–26**	**–104**
WI PSNT 45	-	-	-	–140	39	–101
Canopy Reflectance sensing	-	-	-	**–144**	**45**	**–99**

† Indicates that each state used their respective state yield goal recommendation

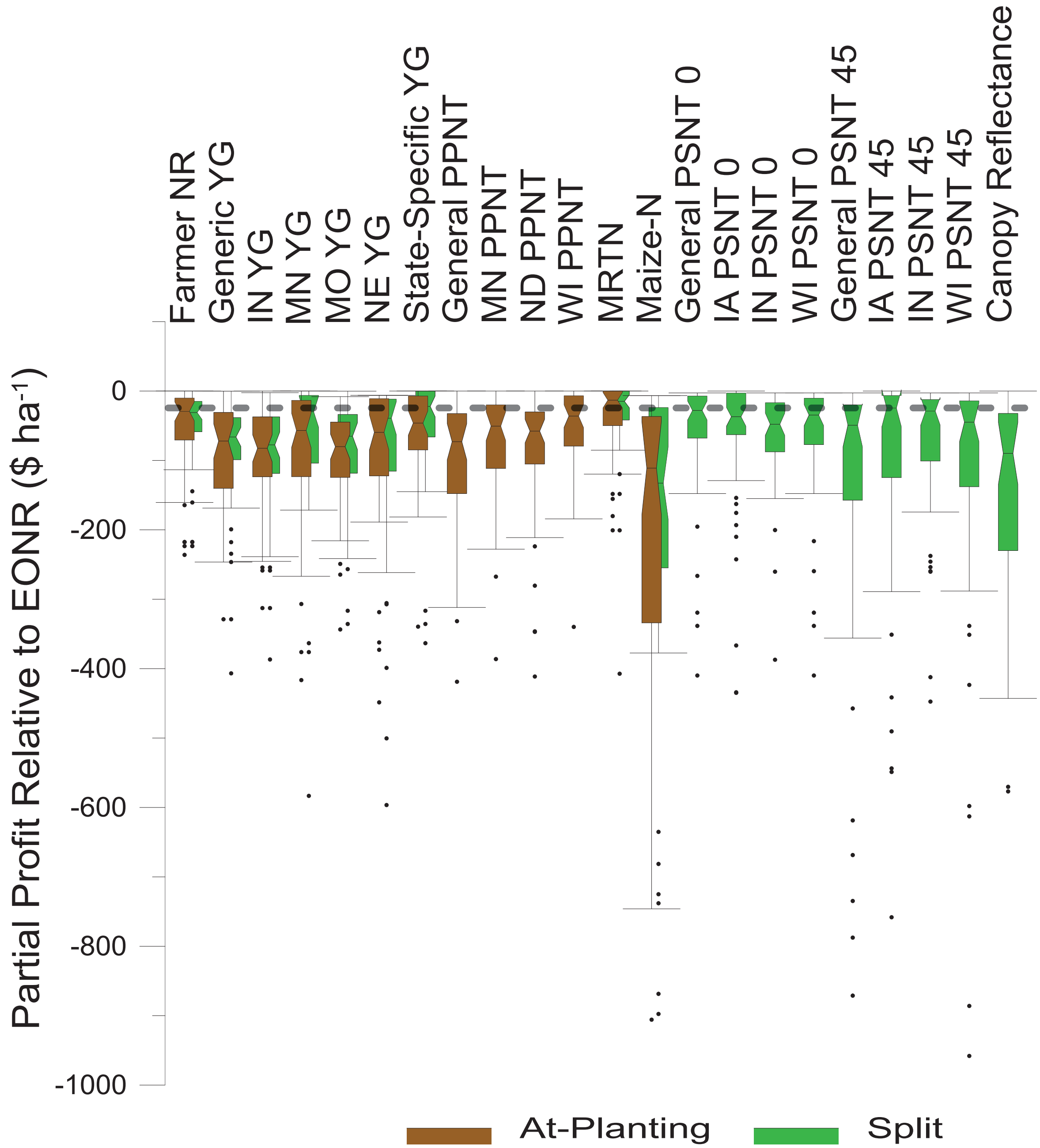

Fig. A1. Partial profit for N recommendation tools relative to the economically optimal N rate (EONR). Both at-planting and split N application tools are shown. Tool descriptions include YG as yield goal, PPNT as pre-plant nitrate test, and PSNT 0 and PSNT 45 as the pre-sidedress nitrate test with 0 and 45 kg N ha^{-1} applied at-planting, respectively. Notches on the side of each the box indicate the 95% confidence interval around the median. Limits of the box indicate the first and third quartile, whiskers indicate 1.5 × IQR, and small circles indicate outliers.

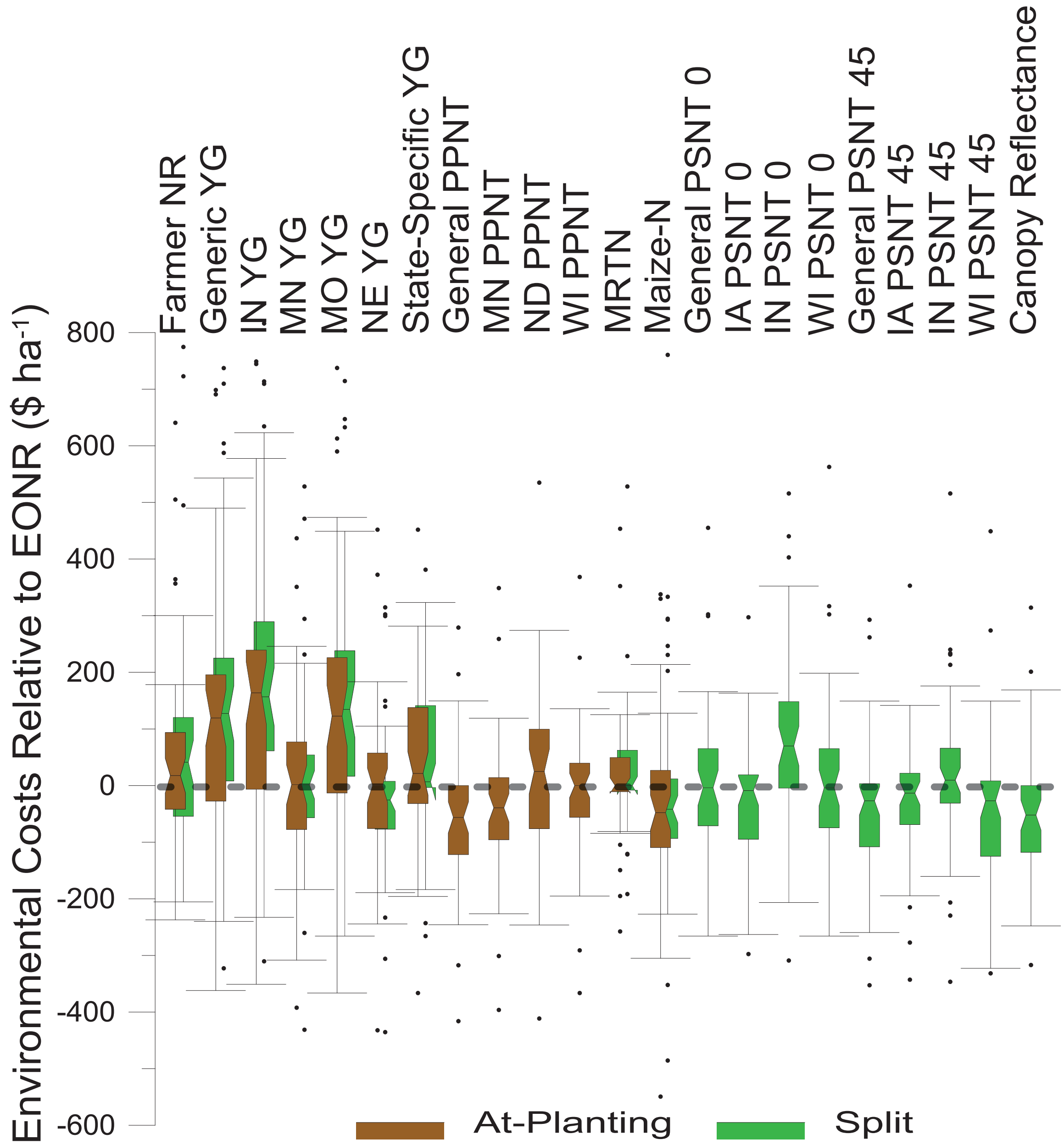

Fig. A2. Environmental costs for N recommendation tools relative to the economically optimal N rate (EONR). Both at-planting and split N application tools are shown. Tool descriptions include YG as yield goal, PPNT as pre-plant nitrate test, and PSNT 0 and PSNT 45 as the pre-sidedress nitrate test with 0 and 45 kg N ha^{-1} applied at-planting, respectively. Notches on the side of each the box indicate the 95% confidence interval around the median. Limits of the box indicate the first and third quartile, whiskers indicate 1.5 × IQR, and small circles indicate outliers.

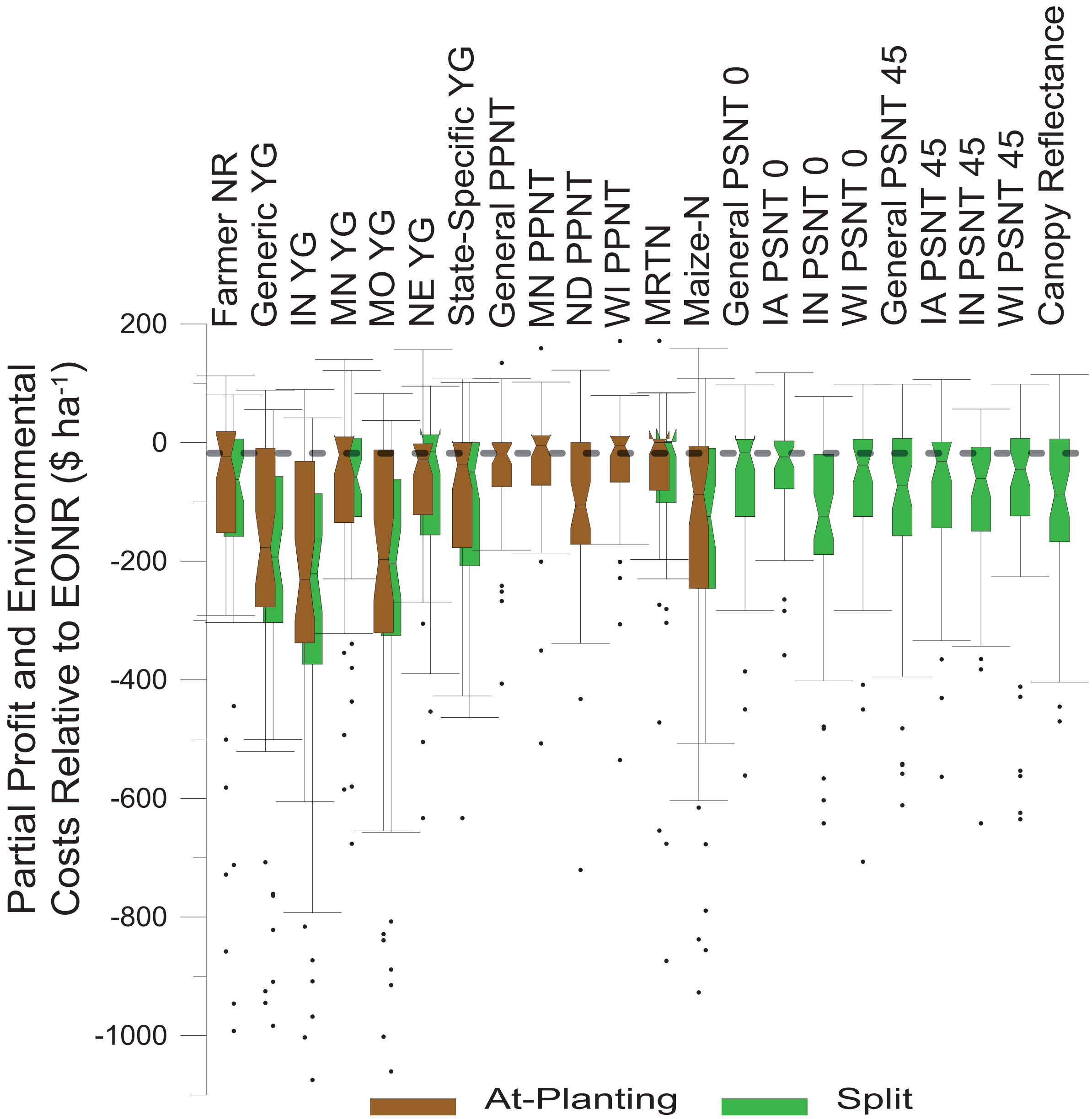

Fig. A3. Combined partial profit and environmental costs for N recommendation tools relative to the economically optimal N rate (EONR). Both at-planting and split N application tools are shown. Tool descriptions include YG as yield goal, PPNT as pre-plant nitrate test, and PSNT 0 and PSNT 45 as the pre-sidedress nitrate test with 0 and 45 kg N ha^{-1} applied at-planting, respectively. Notches on the side of each the box indicate the 95% confidence interval around the median. Limits of the box indicate the first and third quartile, whiskers indicate 1.5 × IQR, and small circles indicate outliers.

VITA

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