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Strengths and Limitations of Nitrogen Rate Recommendations for Corn and Opportunities for Improvement

Thomas F. Morris,* T. Scott Murrell, Douglas B. Beegle, James J. Camberato, Richard B. Ferguson, John Grove, Quirine Ketterings, Peter M. Kyveryga, Carrie A.M. Laboski, Joshua M. McGrath, John J. Meisinger, Jeff Melkonian, Bianca N. Moebius-Clune, Emerson D. Nafziger, Deanna Osmond, John E. Sawyer, Peter C. Scharf, Walter Smith, John T. Spargo, Harold M. van Es, and Haishun Yang

ABSTRACT

Nitrogen fixation by the Haber–Bosch process has more than doubled the amount of fixed N on Earth, significantly influencing the global N cycle. Much of this fixed N is made into N fertilizer that is used to produce nearly half of the world's food. Too much of the N fertilizer pollutes air and water when it is lost from agroecosystems through volatilization, denitrification, leaching, and runoff. Most of the N fertilizer used in the United States is applied to corn (*Zea mays* L.), and the profitability and environmental footprint of corn production is directly tied to N fertilizer applications. Accurately predicting the amount of N needed by corn, however, has proven to be challenging because of the effects of rainfall, temperature, and interactions with soil properties on the N cycle. For this reason, improving N recommendations is critical for profitable corn production and for reducing N losses to the environment. The objectives of this paper were to review current methods for estimating N needs of corn by: (i) reviewing fundamental background information about how N recommendations are created; (ii) evaluating the performance, strengths, and limitations of systems and tools used for making N fertilizer recommendations; (iii) discussing how adaptive management principles and methods can improve recommendations; and (iv) providing a framework for improving N fertilizer rate recommendations.

Core Ideas

- Nitrogen recommendations for individual corn fields are less accurate than desired.
- Nitrogen recommendations need improvement for economic and environmental reasons.
- A review of fundamental concepts will improve understanding about N recommendations.
- Examination of N recommendation systems, tests, and models will improve recommendations.

THE GOAL of an N recommendation system is to accurately estimate the gap between the N provided by the soil and the N required by the plant. Accurately estimating this gap depends on the ability of the recommendation system to accurately estimate field or subfield specific economically optimal nitrogen rates (EONR). Current recommendation systems are not as accurate as needed to provide consistently reliable estimates of N needs across years at the field or subfield scale. Uncontrollable factors like temperature, rainfall timing, intensity and amount, and interactions of temperature and rainfall with factors such as N source, timing and placement, plant genetics, and soil characteristics combine to make N rate recommendations for an individual field or rates for subfields a process guided as much by science as by the best professional judgement of farmers and farm advisors.

Substantial evidence has accumulated that EONRs can vary widely across fields, within fields and over years in the same field for a wide range of crops and geographies. Examples

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Abbreviations: BBC, biological buffering capacity; CSNT, corn stalk nitrate test; EONR, economic optimal nitrogen rate; MRTN, maximum return to nitrogen; PNM, precision nitrogen management; RTN, return to nitrogen; RMSE, root mean square error; SOM, soil organic matter.

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specific to corn in the United States are the field-to-field variability reported by Bundy and Andraski (1995), Schmitt and Randall (1994), and Lory and Scharf (2003), and year-to-year variability across fields reported by Dhital and Raun (2016). Equally important are reports documenting wide within-field variability in EONRs (Schmidt et al., 2002; Mamo et al., 2003; Scharf et al., 2005; Schmidt et al., 2007; Cao et al., 2012). These studies suggest that the variability is often quite large over small distances, and the most instructive example shows (Fig. 1) quite different optimal N rate patterns for two different years in the same field (Mamo et al., 2003).

The EONR varies within fields and across fields and years primarily due to interactions among soil properties and environmental conditions (Tremblay et al., 2012). Accurate recommendation systems are needed to optimize economic returns for farmers; maintain or increase yield required to meet food, feed, fiber, and fuel demands of societies; and preserve the long-term functionality of terrestrial and aquatic ecosystems. Large variation in EONRs greatly complicates attaining these goals.

Creating more accurate N recommendations for individual corn fields is difficult because the complexity of the N cycle affecting individual fields (Fig. 2) complicates predictions of plant-available N, which is the amount of residual N plus mineralized N produced by the soil organic matter in a field minus the amount of N lost from the root zone during the growing

season. The only part of the cycle that can be managed completely is the N fertilizer application. If organic N is applied there is often uncertainty about the rate of N application and greater uncertainty about the availability of the organic N to the soil–plant–atmospheric system. Many of the transformations of N in the cycle are not manageable by farmers because the transformations are biological processes dependent on soil properties and driven by field-specific weather events.

Current N recommendation systems assume an average uptake of about 35 to 75% of N fertilizer applied to corn (Meisinger, 1984; Cassman et al., 2002; Ketterings et al., 2003). These values are based mostly on research with ^{15}N tagged fertilizer where recoveries of N in corn grain ranges from 13 to 45%, and the amount not recovered in the soil–plant system ranges from 23 to 64% (Olson, 1980; Kitur et al., 1984; Sanchez and Blackmer, 1988; Varvel and Peterson, 1990). There is much concern about unrecovered N fertilizer percentages that range from 23 to 64%, which is 40 to 108 kg N ha⁻¹ if a rate of 168 kg N ha⁻¹ is applied, because N that is not recovered in the root zone can lead to water and air pollution. Knowledge and experience with the strengths and limitations of current corn N fertilizer recommendations is important for the development of future recommendation systems that better estimate field-to-field, within-field, and year-to-year variability in EONRs.

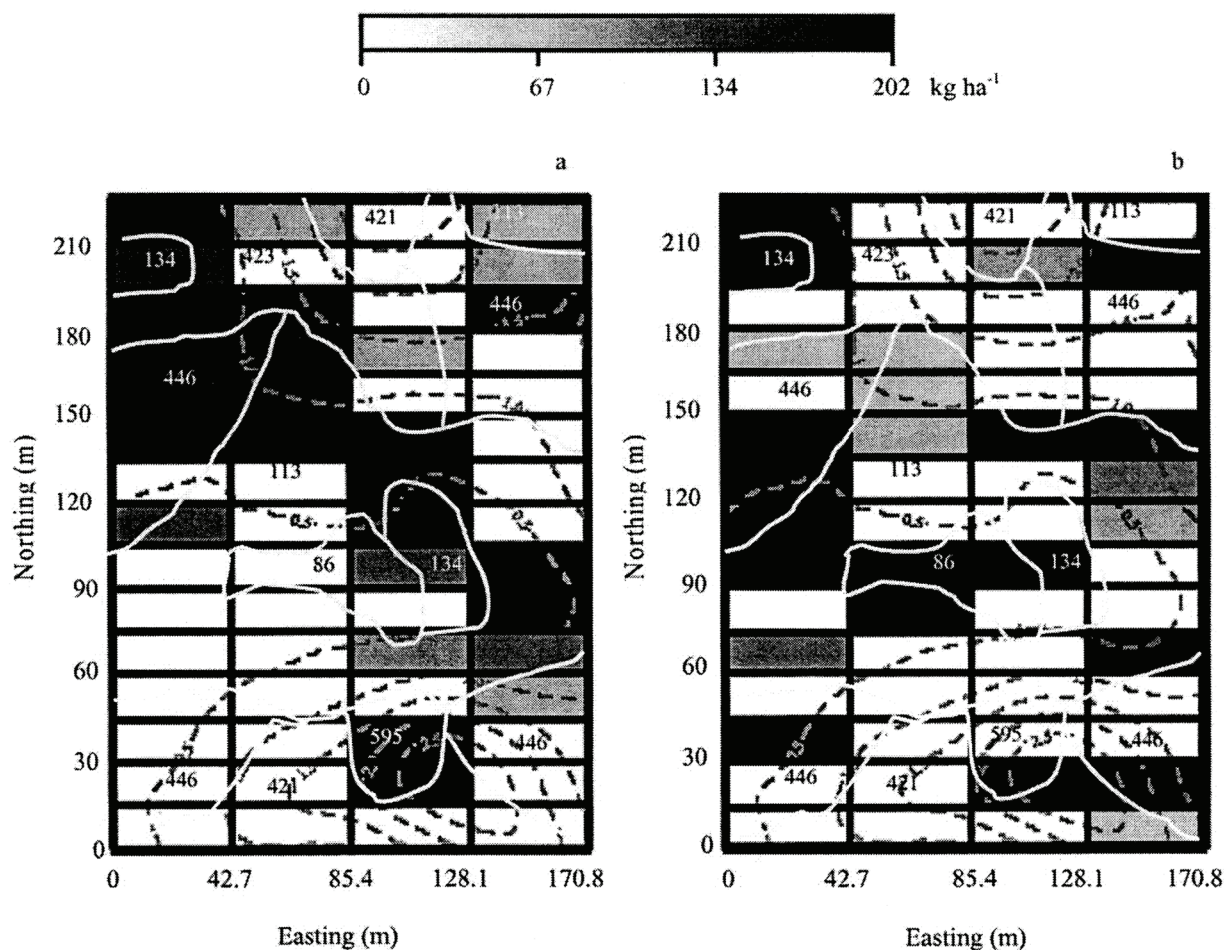


Fig. 1. Spatial distribution of economically optimum nitrogen rate (EONR) determined by variable response curve models for corn yield in (a) 1997 and (b) 1999 overlaid with the soil and elevation of the field. (Soil: 86, Canisteo clay loam; 113, Webster clay loam; 134, Okoboji silty clay loam; 421, Ves loam; 423, Seaforth loam; 446 Normania loam; 595, Swanlake loam). (Mamo et al., 2003).

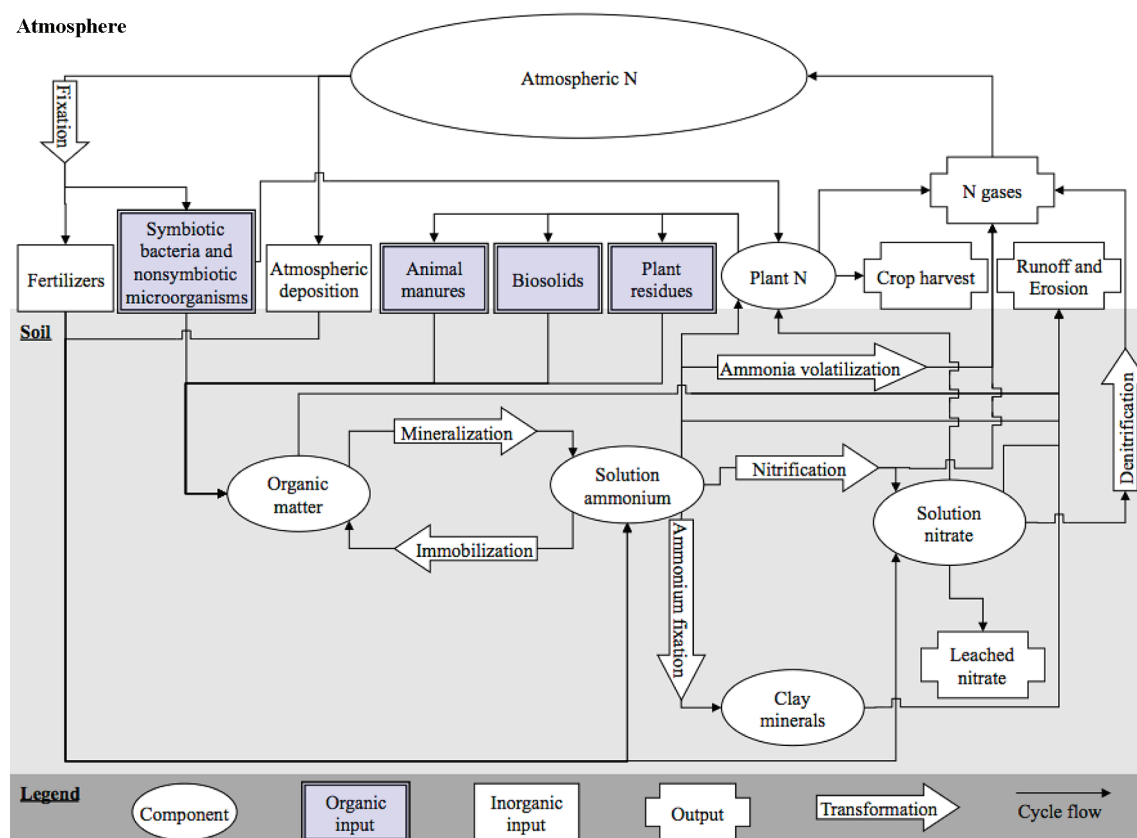


Fig. 2. Diagrammatic representation of the N cycle operating at the field scale.

The objectives of this paper were to review current methods for estimating N needs of corn by: (i) reviewing fundamental background information about how N recommendations are created; (ii) evaluating the performance, strengths, and limitations of systems and tools used for making N fertilizer recommendations; (iii) discussing how adaptive management principles and methods can improve recommendations; and (iv) providing a framework for improving N fertilizer rate recommendations.

FUNDAMENTAL BACKGROUND INFORMATION ABOUT NITROGEN RECOMMENDATIONS

A logical starting point for creating N recommendations is the total quantity of N a plant must accumulate to complete its life cycle (N_y). Total N accumulation has conventionally been divided into two major plant portions: (i) aboveground biomass (leaves, stems, and grains) and (ii) belowground biomass (roots). Aboveground N accumulation is the only portion that can be measured routinely under field conditions and for this reason the total quantity of N that a plant must accumulate to complete its life cycle (N_y) has been used as a proxy for total N accumulation.

Estimating N_y is typically done by measuring total aboveground N accumulation of fertilized plants (U). However, N_y cannot be equated to U directly because for a given level of yield, plant N content can vary in concentration. Lower concentrations can result when N fertilization is nutritionally limiting or when N stimulates greater biomass production that dilutes N concentration (Janssen et al., 1990; Jarrell and Beverly, 1981). Higher concentrations can result from N rates that were nutritionally excessive or from the presence of other

yield-limiting factors (Janssen et al., 1990). Consequently, N recommendations relying on N_y estimates should use measurements of U that are close to nutritionally optimum.

Soil systems supply a portion of the total N accumulated by plants. Figure 2 shows that soil N originates from several sources: past N applications, crop residues, atmospheric deposition, microorganisms, and organic matter. The contribution of soil N in the total N supply to the plant (N_s) is variable, but often soil N supplies a greater amount of N than contributed by N fertilizer applications (Cassman et al., 2002). A common measurement to estimate N_s is the uptake of N by plants not fertilized with N (U_0). Equating N_s to U_0 assumes that no interactions occur to increase or decrease N_s when the plants are fertilized. However, there is evidence that N fertilization may affect the N cycle in ways that cause N_s to differ from U_0 , indicating that N fertilization can stimulate N mineralization from organic matter (the priming effect) and reduce the quantity and rate of N immobilization by crop residues (Broadbent, 1965; Jenkinson et al., 1985; Green and Blackmer, 1995; Hgaza et al., 2012). Future recommendation systems might need to take these interactions into account.

Almost all N recommendation systems for corn in the United States from the 1970s until 2005 were based on Stanford's ideas (1966, 1973). His approach is known by various names including the "yield goal", "expected yield", or "yield based" method of making a N recommendation, where the purpose of a fertilizer N application is to provide the quantity of N needed by the plant that is not provided by the soil. A newer method to estimate the quantity of N needed by plants not provided by the soil, the maximum return to nitrogen

(MRTN) method, was introduced in 2005 in seven states in the Corn Belt where a large majority of the rainfed corn in the United States is planted (Sawyer et al., 2006). The MRTN method will be described later in this paper. Stanford's ideas about yield goal will be used in this introduction as a vehicle to describe and explain the complexity of creating N recommendations for individual fields.

The nutritional need for N by plants is quantified by subtracting N_s from N_y . This difference ($N_y - N_s$) is the quantity of fertilizer N that must be taken up by the plant, however, it is typically not the rate that needs to be applied. The N application rate (N_f) is usually greater because not all of the applied N is taken up by the plant. The fraction of applied N taken up, a decimal less than one, is termed "recovery efficiency" (E_f). Therefore, to calculate a N rate to apply, the nutritional need of the plant is adjusted by the efficiency with which an N application is utilized by the plant. Stanford expressed these relationships in the following equation:

$$N_f = (N_y - N_s)/E_f \quad [1]$$

The presence of the fractional E_f in the denominator adjusts N_f upward beyond the plant nutritional need.

The recovery efficiency E_f is not directly measurable. The observational estimate typically used to approximate E_f is the "apparent crop recovery efficiency" (RE_N) (Cassman et al., 2002). This efficiency is calculated by the difference method: subtracting U_0 from U and dividing by N_f , which gives:

$$RE_N = (U - U_0)/N_f \quad [2]$$

An estimate of average RE_N for corn near the EONR in the north-central United States is 0.37 ± 0.30 (± 1 SD; Cassman et al., 2002). Across several regions, the global RE_N average is 0.65 ± 0.03 (\pm SE; Ladha et al., 2005). The RE_N average of only 37% is due to the complex processes affecting N after fertilizer is applied to a field. The N can be: leached, denitrified, incorporated in SOM, fixed in clay minerals, or volatilized (Fig. 2). Re-arranging Eq. [2] transforms Stanford's original equation (Eq. [1]) into measurable estimates:

$$N_f = (U - U_0)/RE_N \quad [3]$$

While Eq. [3] provides a clear conceptual model, its direct usefulness for making N fertilizer recommendations is limited by the current lack of accuracy in predicting U , U_0 , and RE_N for a given field and crop year. The crop uptake (U) is estimated primarily by the crop yield, which is very difficult to predict for a given year. Additionally, RE_N can vary depending on the fertilizer source, method, and timing of application (Burzaco et al., 2014; Maddux et al., 1991) as influenced by site-specific environmental factors such as soil properties and climate, with rainfall after N application the primary driver of variability in RE_N .

A simplified version of Eq. [3] has been used in many algorithms to estimate the amount of N fertilizer to apply. This version typically assumes constant values for U_0 and RE_N and assumes that U is directly proportional to yield. This results in an empirical factor n , known as the internal N requirement of corn, which was first suggested by Stanford (1973) based

on data from one of his previous studies (Stanford, 1966). The data showed that on average the "...maximum attainable yield was associated with 1.2% N in total dry matter" (Stanford, 1973). Stanford then placed U on a grain yield (Y_G) basis and labeled the resulting quotient n , which represented the average quantity of total N taken up per harvest unit of grain [$\text{kg N (kg grain)}^{-1}$]:

$$n = U/Y_G \quad [4]$$

The average value of n was $2.1 \times 10^{-2} \pm 0.2 \times 10^{-2}$ kg N (kg grain^{-1}), or 1.2 ± 0.1 lb N bu $^{-1}$. This value was derived assuming: (a) a yield of 6278 kg ha $^{-1}$ (100 bu acre $^{-1}$); (b) a bushel of corn weighed 25.5 kg (56 lb) at 120 g kg $^{-1}$ moisture (DM basis); and (c) a harvest index (DM basis) of approximately 0.5. Changing the moisture from 120 g kg $^{-1}$ moisture to the 155 g kg $^{-1}$ currently used for reporting corn grain yield changes the value of n slightly, but it still rounds to 2.1×10^{-2} kg N (kg grain^{-1}). This value of n has been widely used as a constant in N recommendation algorithms.

The efficiency with which corn plants use N to produce grain biomass [$\text{kg grain (kg N)}^{-1}$] was termed nitrogen internal efficiency (NIE) by Ciampitti and Vyn (2012), which is defined as:

$$NIE = Y_G/U \quad [5]$$

Comparing Eq. [4] and [5] shows that:

$$n = 1/NIE \quad [6]$$

This inverse relationship implies that, for a given level of Y_G , if a corn plant is able to produce more grain per unit of total N uptake (NIE becomes larger), the internal N requirement is reduced (n becomes smaller). The NIE of old era (1940–1990) and new era (1991–2011) hybrids were compared by Ciampitti and Vyn (2012). Old era hybrids had an average NIE of 49.7 ± 10.0 kg grain (kg N^{-1}) or 0.888 ± 0.179 bu (lb N) $^{-1}$, assuming 15.5% moisture and a test weight of 56 lb grain bu $^{-1}$. Thus n for the old era hybrids was $2.01 \times 10^{-2} \pm 4.05 \times 10^{-3}$ kg N (kg grain^{-1}), or 1.13 ± 0.22 lb N bu $^{-1}$. The average NIE of new era hybrids was 56.0 ± 13.5 kg grain (kg N^{-1}) or 1.00 ± 0.241 bu (lb N) $^{-1}$ and an n of $1.79 \times 10^{-2} \pm 4.30 \times 10^{-3}$ kg N (kg grain^{-1}), or 1.00 ± 0.241 lb N bu $^{-1}$.

The version of Stanford's equation historically used in the U.S. Corn Belt for estimating N fertilizer needs is based on yield goal (Y_{GOAL}) (Lory and Scharf, 2003). The basic equation is:

$$N_f = n(Y_{GOAL}) \quad [7]$$

Fertilizer recommendations using this equation are directly proportional to yield, however, such simple proportionality is rarely observed in practice (Vanotti and Bundy, 1994a, Fox and Piekielek, 1995, Lory and Scharf, 2003). As the original form of the Stanford equation shows, N_f is proportional to the *difference* between crop N uptake and the amount of that uptake met by the soil N supply (Eq. [3]), or the unmet N need. Yield goal-based recommendations are not commonly adjusted by RE_N , which means the recommendation is not adjusted for the

form, timing, and placement of N fertilizer. Yield goal recommendations are adjusted for manure applications and previous crop, which are based on empirically estimated N credits (Bundy, 2008).

In most recommendation systems, empirical adjustments or “credits,” calculated as fertilizer equivalents, are made to account for other sources of N that contribute to the N uptake by corn and thereby reduce N_f . Because these credits are in fertilizer equivalents, they represent the product of the amount of a given N source that is plant available (Q) and the fraction of that supply taken up by corn, which is an efficiency parameter (E).

As an example, many N recommendations include a “legume credit.” This credit is calculated from N rate studies that compare the response of continuous corn to corn grown in rotation with a legume. The legume lowers the optimum rate of N for corn. The level of the legume nitrogen reduction (N_{LN} , kg ha⁻¹) is determined empirically, however, theoretically, it arises from the portion of the soil N supply attributable to the effects of the legume (Q_{LN}) and the fraction of that supply used by the plant (E_{LN}):

$$N_{LN} = Q_{LN} \times E_{LN} \quad [8]$$

Equation [7] is usually expanded to include more factors that reduce N_f from U . Other possibilities for fertilizer-equivalent factors are: residual N from legumes grown earlier than the previous cropping season (N_{RLN}); manure inorganic nitrogen from fresh applications (N_{MIN}), manure organic nitrogen from fresh applications (N_{MON}), residual organic nitrogen from past manure applications (N_{RMON}), soil nitrate (N_{SNO3}), soil organic matter (N_{SOM}), and residual soil nitrate N_{RNO3} :

$$N_f = n(Y_{GOAL}) - N_{LN} - N_{RLN} - N_{MIN} - N_{MON} - N_{RMON} - N_{SNO3} - N_{SOM} - N_{RNO3} \quad [9]$$

All of these fertilizer-equivalent factors can be expressed analogously to Eq. [8] to make explicit the theoretical concepts of quantity and efficiency of each source of N:

$$N_f = n(Y_{GOAL}) - (Q_{LN} \times E_{LN}) - (Q_{RLN} \times E_{RLN}) - (Q_{MIN} \times E_{MIN}) - (Q_{MON} \times E_{MON}) - (Q_{RMON} \times E_{RMON}) - (Q_{SNO3} \times E_{SNO3}) - (Q_{SOM} \times E_{SOM}) - (Q_{RNO3} \times E_{RNO3}) \quad [10]$$

The availability of the organic sources of N in Eq. [10] (Q_{LN} , Q_{RLN} , Q_{MON} , Q_{RMON} , and Q_{SON}) are largely controlled by mineralization and immobilization processes. These organic sources of N have always been thought to need mineralization to inorganic N before the N is available for plant uptake. However, recent evidence suggests organic N in the form of amino acids may supply N to plants, especially in organic cropping systems (Grantham, 2015). Whether the amount of N supplied by amino acids is important for plant nutrition is uncertain (Nasholm et al., 2009), but future research may show a need to include organic N in N fertilizer recommendations.

How much organic N will be mineralized during the growing season determines the size of Q for these sources. Just like inorganic forms of N, the fraction of the N taken up by corn

from these sources is accounted for by efficiency factors (E) (Meisinger, 1984; Meisinger et al., 1992b). The Q and E factors in Eq. [10] can be used mechanistically to estimate the contribution of each N source to plant uptake rather than to provide fertilizer-equivalent credits. In this case, they represent components of U_0 in Eq. [3]. When used this way, the Q and E factors can be substituted into Eq. [3], which puts RE_N back into the determination of N_f :

$$N_f = [U - (Q_{LN} \times E_{LN}) - (Q_{RLN} \times E_{RLN}) - (Q_{MIN} \times E_{MIN}) - (Q_{MON} \times E_{MON}) - (Q_{RMON} \times E_{RMON}) - (Q_{SNO3} \times E_{SNO3}) - (Q_{SOM} \times E_{SOM}) - (Q_{RNO3} \times E_{RNO3})] / RE_N \quad [11]$$

Estimating N_f by using Eq. [11], however, is not possible because current knowledge and technologies cannot accurately estimate the almost infinite combinations of Q and E factors for soil, weather, manure, and legumes that affect the amount of N needed for individual corn fields (Fig. 3). For this reason, yield goal-based N recommendation systems are still based on Eq. [9] where a yield goal is multiplied by a factor, usually between 1.79 and 2.14×10^{-2} kg N (kg grain)⁻¹ (1.0 and 1.2 lb N bu⁻¹), with empirically estimated credits for manure applications and previous crop subtracted from the base recommendation.

Two other complicating factors make it difficult to accurately estimate N needs of any crop. Soil-plant N resiliency is the capacity of the soil-plant system to vary plant available N with growing conditions, and biological buffering capacity (BBC), which is a refinement of the soil resiliency concept that rests on the view that the crop is not merely a passive sink for N (Meisinger and Timlin, 2007; Meisinger et al., 2008).

Biological buffering capacity recognizes that crop yield and N uptake involves closely linked soil-crop interactions that are affected by growing-season weather with the plant being the avenue for transmitting the weather effects into modifications of soil-crop interactions. An example of BBC is given in Fig. 4, which shows how apparent soil N supply (as estimated by non-fertilized corn yield) can vary with different growing-season weather and different soils. The upper panel in Fig. 4 is a plant-soil system that has low BBC with unfertilized yields being unchanged in low-, medium-, and high-yielding years; that leads to a resulting yield response (delta yield) and an economic optimum that increases or decreases, in high-yielding or low-yielding years, respectively. The lower panel in Fig. 4 is an example of high BBC with unfertilized yields increasing in high-yielding years and the resulting delta yield and economic optimum being similar in both high- and low-yielding weather.

Biological buffering capacity is difficult to measure and currently is impossible to measure for all combinations of soils and environmental conditions. Biological buffering capacity affects the amount of supplemental N needed by increasing the N supply when growing conditions are favorable, and decreasing the amount assumed to be made available over the growing season when growing seasons are unfavorable. When growing conditions are favorable, yields are typically greater, but because the soil supplies more N with favorable conditions, less N is needed from fertilizer or other sources applied by farmers. Biological buffering capacity can be accounted for by the n , Q ,

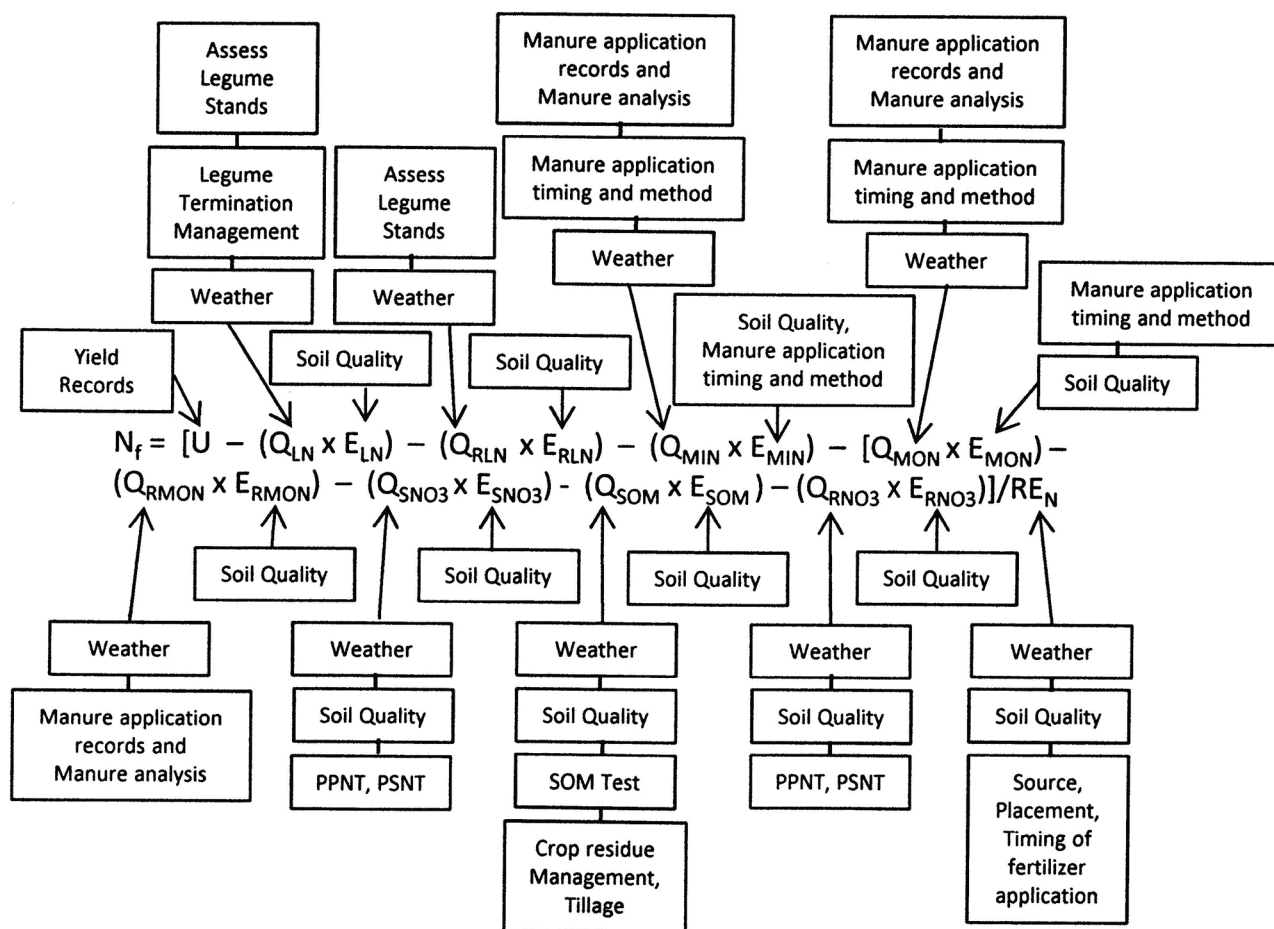


Fig. 3. Fig. 3. Soil, weather, manure and legume factors that interact to create an almost infinite combination of factors that make it impossible with current knowledge and technologies to accurately estimate the amount of N fertilizer to apply to an individual field. N_f , nitrogen application rate; U , total aboveground nitrogen of fertilized plants; Q , plant available nitrogen; E , efficiency parameter; LN, legume nitrogen; RLN, residual legume nitrogen; MIN, manure inorganic nitrogen; MON, manure organic nitrogen; RMON, residual manure organic nitrogen; SNO₃, soil nitrate nitrogen; SOM, soil organic matter; RSNO₃, residual soil nitrate nitrogen; RE_N, apparent crop recovery efficiency; PPNT pre-plant soil nitrate test; PSNT, pre-sidedress soil nitrate test.

and E factors in Eq. [10]. A number of interacting factors likely cause BBC including: better temperature and moisture conditions for organic N mineralization (increased Q); less leaching and denitrification losses due to less extreme soil moisture conditions (increased Q); larger root systems with greater mass flow to enhance N uptake (increased E); and greater portioning of dry matter to shoots than roots thus increasing yield with the same N (decreased n). The effect of BBC on N fertilizer requirements has been shown to decrease the expected amount of N fertilizer needed by the crop (Fox and Piekielek, 1995; Schlegel et al., 1996; Vanotti and Bundy, 1994a), and the effect is discussed in detail by Meisinger et al. (2008).

This review of the ideas and the equations describing those ideas supporting N recommendations by the yield goal method show that creating accurate N recommendations for individual fields is a difficult task. Much greater knowledge about fundamental mechanisms of the N cycle in soils and how to apply that knowledge to individual fields are needed to improve N recommendations. Improvement of N fertilizer recommendations should be a national priority due to the effect of the recommendations on U.S. and world food production and economies, the tremendous increase in grain yield per unit of land from N applications, and the need to protect and improve

ground and surface water quality. As a first step to improving N recommendations, we provide a review of current methods for making recommendations and the tools used to enhance the recommendations. We then propose a method of adaptive management to enable farmers to learn over time what is a reasonable estimate of a rate for individual fields or parts of fields, and lastly, we provide a framework for improving N fertilizer rate recommendations.

SYSTEMS AND TOOLS USED TO MAKE NITROGEN RECOMMENDATIONS

Yield-Based Nitrogen Recommendations for Corn

Stanford's equation of expected grain yield or yield goal and N_f as described in Eq. [7] underpinned all N recommendations at Land Grant Universities until development of the maximum return to nitrogen (MRTN) system of N recommendations (Sawyer et al., 2006). Currently, Land Grant Universities in 34 states (Fig. 5) make N recommendations based on a derivation of Stanford's equation, representing 41% of the planted corn land area and 35% of the grain harvested in the United States (National Corn Growers Association, 2017). Kentucky does not use either yield goal or MRTN approaches, but rather groups results of numerous corn N response studies, and makes

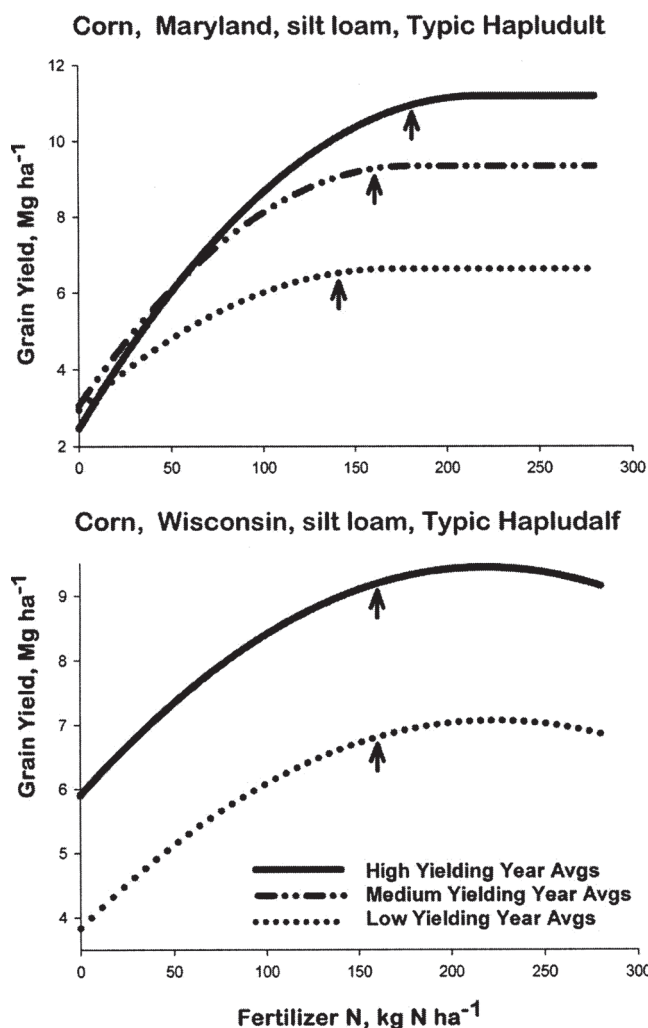


Fig. 4. Average corn grain yields vs. fertilizer N applied in low-, medium-, or high-yielding years for quadratic-plateau response in Maryland (upper panel) from 21-yr of data (Meisinger and Timlin, 2007), and for a quadratic response in Wisconsin (lower panel) from 24-yr of data (Vanotti and Bundy, 1994b). Arrows indicate estimated economic optimum N rates.

corn N recommendations according to previous crop, soil drainage, and tillage system (University of Kentucky, 2015). Tennessee offers corn N recommendations by both the MRTN (Savoy and Joines, 2015) and yield goal (Mooney et al., 2009) methods.

Every factor for the yield-based N recommendation systems shown in Eq. [10] varies substantially from state to state. The most common factors that vary include methods to establish yield expectation (Y_{goal}), the internal N efficiency (n), and subtractions and additions for residual soil N (N_{SNO_3}), mineralized organic matter-derived N (N_{SOM}), and previous crop. Some states also include a tillage factor that was not included in Stanford's original equations.

Calculating the Base Nitrogen Recommendation

Yield Expectation

The method for determining yield expectation varies considerably from state to state. A number of states provide no guidance on how to set the yield expectation while others provide varying rationales for determining yield expectation. For example, Maryland (McGrath, 2010) suggests a rather



- Yield goal system.
- Maximum return to nitrogen (MRTN).
- ▲ Other, primarily methods based on soil properties.
- ★ Not available.

Fig. 5. Nitrogen recommendation systems used in the United States. The states of Massachusetts, Connecticut, Rhode Island, Maryland, and Delaware use the yield goal system.

open-ended rationale: “a realistic target yield that is achievable given favorable growing conditions”. Other states suggest a more quantitative approach to establishing the yield expectation such as the 5-yr average, the 5-yr average ± 5 to 10% in Nebraska (Shapiro et al., 2008), or the expected yield in 3 to 4 yr out of 5 under good management in New York (Ketterings et al., 2003; NCINMC, 2014). South Dakota (Reitsma et al., 2008) provides several approaches to determining expected yield—the 5-yr average minus outliers (referred to as proven yield), proven yield +10%, proven yield modified for soil moisture (± 10 –20%), or modified county averages. The expectation that average corn grain yield will continue to increase from year to year and the opportunity to make high yields when environmental conditions are conducive are two factors mentioned for rationalizing an N rate above that calculated from a short-term average yield.

Internal Nitrogen Requirement

The n in Eq. [4], is estimated by using an expected amount of N uptake bu^{-1} of grain. In yield-based N recommendation systems, the yield goal or expectation (Y_{GOAL}) is multiplied by n to estimate (N_f) as in Eq. [7]. Several states (Georgia, Montana, New York, South Dakota) utilize $2.14 \times 10^{-2} \text{ kg N (kg grain)}^{-1}$ (1.2 lb N bu^{-1}) to multiply the yield expectation (University of Georgia, 2008; Jacobsen et al., 2005; Ketterings et al., 2003; Reitsma et al., 2008), but others use different values. Several states in the eastern United States use between 1.79×10^{-2} and $2.23 \times 10^{-2} \text{ kg N (kg grain)}^{-1}$ (1.0 and $1.25 \text{ lb N bu}^{-1}$); including Maryland (McGrath, 2010), Pennsylvania (Beegle, 2015), Tennessee (Savoy and Joines, 2015), and Virginia (Alley et al., 2009). The lowest recommended ranges for n are those of Florida (Wright et al., 2014) [1.43×10^{-2} to $2.14 \times 10^{-2} \text{ kg N (kg grain)}^{-1}$ or 0.8 – 1.2 lb N bu^{-1}], Vermont (Jokela et al., 2004; 1.61×10^{-2} to $1.79 \times 10^{-2} \text{ kg N (kg grain)}^{-1}$ or 0.9 – 1.0 lb N bu^{-1}),

and North Carolina [Rajkovich et al., 2015; 1.43×10^{-2} to 1.79×10^{-2} kg N (kg grain) $^{-1}$ or 0.8–1.0 lb N bu $^{-1}$].

States using values of n greater than 2.14×10^{-2} are located mostly in the western United States and have dry climates. Examples are 2.86×10^{-2} kg N (kg grain) $^{-1}$ (1.6 lb N bu $^{-1}$) in Kansas (Leikam et al., 2003), Utah (Topper et al., 2010), and Wyoming (Blaylock et al., 1996), 2.50×10^{-2} to 2.68×10^{-2} kg N (kg grain) $^{-1}$ (1.4–1.5 lb N bu $^{-1}$) in Idaho, Washington, and Oregon (Brown et al., 2010), and 2.32×10^{-2} kg N (kg grain) $^{-1}$ (1.3 lb N bu $^{-1}$) in Mississippi (Oldham, 2012).

Some states vary n with yield level, usually decreasing it with increased yield expectation. Idaho (Brown et al., 2010) and South Carolina (Clemson University, 2007) decrease the factor approximately 0.18×10^{-2} to 0.36×10^{-2} kg N (kg grain) $^{-1}$ (0.1–0.2 lb N bu $^{-1}$) across yield levels ranging from 6300 to 12,500 kg grain ha $^{-1}$ (100–200 bu acre $^{-1}$). In contrast, Oklahoma (Zhang et al., 2009) increases the factor with increased yield goal from 1.79×10^{-2} kg N (kg grain) $^{-1}$ (1.0 lb N bu $^{-1}$) at expected yields less than 6300 kg grain ha $^{-1}$ (100 bu acre $^{-1}$) to 2.14×10^{-2} kg N (kg grain) $^{-1}$ (1.2 lb N bu $^{-1}$) at 12,500 kg grain ha $^{-1}$ (200 bu acre $^{-1}$). Texas (Texas A&M, 2012) recommendations range from 1.79×10^{-2} and 2.32×10^{-2} kg N (kg grain) $^{-1}$ (1.0–1.3 lb N bu $^{-1}$) across the same yield range.

Missouri is unique in that it varies n based on an assumed plant population required for a given yield level (Brown et al., 2004). For each 2470 plants ha $^{-1}$ (1000 plants acre $^{-1}$) 4.5 kg N ha $^{-1}$ (4 lb N acre $^{-1}$) is added to the base recommendation [1.61×10^{-2} kg N (kg grain) $^{-1}$ (0.9 lb N acre $^{-1}$) \times yield goal]. For example: a Y_{Goal} of 12,500 kg grain ha $^{-1}$ (200 bu acre $^{-1}$) for irrigated corn at an assumed plant population of 64,220 plants ha $^{-1}$ (26,000 plants acre $^{-1}$) results in a N recommendation of: $(1.61 \times 10^{-2}$ kg N (kg grain) $^{-1} \times 12,500 \text{ kg ha}^{-1}) + (4.5 \text{ kg N ha}^{-1} \text{ per } 2470 \text{ plants ha}^{-1} \times 64,220 \text{ plants ha}^{-1}) = 318 \text{ kg N ha}^{-1}$ equivalent to 2.55×10^{-2} kg N (kg grain) $^{-1}$.

Multiplying the Y_{GOAL} by the internal N requirement (n) establishes the bulk of the base N recommendation (N_f) in all yield-based N recommendations. The types and number of adjustments made to the base N recommendation, however, vary considerably among states.

Subtractions and Additions to the Base Nitrogen Recommendation

Subtractions and additions to the base N recommendation are made for several factors, including residual soil NO $_3$ -N, soil N mineralization, irrigation water NO $_3$ -N, and crop rotation and tillage effects, analogous to the expansion of Eq. [7] into Eq. [9]. The factors utilized and the deduction for each factor is state specific.

Nine states (Colorado, Idaho, Kansas, Montana, Nebraska, Oklahoma, South Dakota, Texas, Utah), mostly in the arid and semiarid regions where annual rainfall is less than 64 cm (25 in), recommend reducing the base N recommendation by the amount of residual soil NO $_3$ -N (N_{RNIT}) found to a given depth of soil, suggesting N_{RNIT} has the same efficiency as fertilizer N. The recommended sampling depth is generally 60 cm (2 ft) or greater although some states will use shallower depths like 15 cm (6 in) [Texas (Texas A&M, 2012); Oklahoma

(Zhang et al., 2009)]. Effective rooting depth certainly exceeds 60 cm (2 ft) in most situations, thus only a fraction of the residual NO $_3$ -N available to the crop is considered when sampling less than the full depth of root exploration. Only profile NO $_3$ -N contents exceeding a baseline level are subtracted from the recommendation in South Dakota (Reitsma et al., 2008, deep sampling only).

Seven states, (Colorado, Kansas, Missouri, Montana, Nebraska, New York, Wyoming) making yield-based N recommendations subtract an estimate of SOM-derived N from the base N recommendation as in Eq. [9]. In most states, the estimate is a direct function of percent SOM, but the amount of N credited per percent SOM varies by state. The adjustment to the base N recommendation for SOM-derived N is 22, 22, and 17 to 22 kg N ha $^{-1}$ (20, 20, and 15–20 lb N acre $^{-1}$) per 1% SOM for Kansas (Leikam et al., 2003), Wyoming below 1830 m (6000 ft) elevation (Blaylock et al., 1996), and Montana (Jacobsen et al., 2005—in excess of 2.0% SOM, only), respectively.

In some state recommendation systems, the estimate of SOM-derived N varies with other factors. In Missouri for example, deductions for SOM are altered by texture/cation exchange capacity (CEC). As clay percentage (CEC) increases from sandy loam (<10 cmol $^+$ kg $^{-1}$) to clay loam (>18 cmol $^+$ kg $^{-1}$) the credit for SOM-derived N decreases from 45 to 11 kg N ha $^{-1}$ (40 to 10 lb N acre $^{-1}$) per 1% SOM (Brown et al., 2004). Nebraska and Colorado increase SOM-derived N with increased expected yield (Y_{GOAL}) by the relationship $0.14 \times Y_{\text{GOAL}}$ (bu acre $^{-1}$) \times % SOM, which is equivalent to $2.5 \times 10^{-3} \times Y_{\text{GOAL}}$ (kg ha $^{-1}$) \times % SOM (Shapiro et al., 2008; Davis and Westfall, 2009). Therefore, the N deduction for 2% SOM is 31 kg N ha $^{-1}$ at $Y_{\text{GOAL}} = 6300 \text{ kg grain ha}^{-1}$, vs. 63 kg N ha $^{-1}$ at $Y_{\text{GOAL}} = 12,500 \text{ kg grain ha}^{-1}$. In New York an estimate of soil N contribution is given for each soil series with and without excellent drainage and is based on the percentage of SOM and expected mineralization rate (Ketterings et al., 2003).

In some states, additional N is recommended for corn grown with no-tillage because of lower soil temperatures, slower mineralization, and sequestration in increasing concentrations of soil organic matter. Additions to the standard recommendation for no-till are 11 kg N ha $^{-1}$ (10 lb N acre $^{-1}$) in New York (Ketterings et al., 2003) and 33 kg N ha $^{-1}$ (30 lb N acre $^{-1}$) in Vermont (Jokela et al., 2004).

Nitrogen Credits and Debits Arising from Previous Crop

About half the states reduce yield-based N recommendations by an estimation of a N credit arising from the previous crop. Nitrogen credits are estimated by comparing the N response to fertilizer applications in a corn–corn rotation with the N response in a rotation where corn is planted after a crop other than corn. Reductions for annual legumes such as peanut (*Arachis hypogaea* L.), soybean [*Glycine max* (L.) Merr.], and field pea (*Pisum sativum* L.) ($Q_{\text{LN}} \times E_{\text{LN}}$) are most commonly in the range of 33 to 56 kg N ha $^{-1}$ (30–50 lb N acre $^{-1}$) but are as low as 22 kg N ha $^{-1}$ (20 lb N acre $^{-1}$) (Table 1). Pennsylvania (Beegle, 2015) and Virginia (Alley et al., 2009) calculate the N credit from the previous soybean crop based on yield; with Pennsylvania using $1.67 \text{ kg N (kg soybean grain)}^{-1}$ at 13 g kg $^{-1}$

moisture (1.0 lb N bu⁻¹ soybean yield) and Virginia using 0.83 kg N (kg soybean grain)⁻¹ (0.5 lb N bu⁻¹).

Substantial N credits (>112 kg N ha⁻¹) are given for alfalfa (Table 2) and other perennial legumes grown as forages or cover crops. In many states, the credit is adjusted for the level of stand or percent legume in the sod (Table 2). In some states, N credits are given for 2 and 3 yr after alfalfa plow down, but most only credit 1 yr. In New York (Ketterings et al., 2003), for example, 55, 12, and 5% of the total pool of N available from the alfalfa is credited in Years 1, 2, and 3. South Dakota (Reitsma et al., 2008) credits 50% of the Year 1 credit in Year 2 as well. Nitrogen recommendations for first- or second-year corn grown after alfalfa may be more accurate using the MRTN approach than the yield-goal based method with an alfalfa credit (Morris et al., 1993; Yost et al., 2014) because the BBC of a soil after alfalfa is high. Enhanced BBC and soil-plant resiliency are likely following a deep-rooted perennial legume such as alfalfa (Morris et al., 1993), which will increase the efficiency of N use and corn yield.

When a non-leguminous crop precedes corn, some states increase the base N recommendation. Utah (Topper et al., 2010) recommends an additional 56 kg N ha⁻¹ (50 lb N acre⁻¹) if grain stubble is plowed down and Wyoming (Blaylock et al., 1996) suggests an additional 22 kg N ha⁻¹ (20 lb N acre⁻¹) for every 2.2 Mg ha⁻¹ (1 ton acre⁻¹) of small grain stubble and straw residue or corn stalks (dry) incorporated into the soil.

Evaluation of Yield-Based Recommendations

Evaluation of the accuracy of yield-based N recommendation systems has been limited. Research in seven states in the Midwest currently using the MRTN approach (Bundy, 2006) show poor relationships between yield and EONR, however, these comparisons take into account only achieved yield and thus only evaluate the coefficient of internal N efficiency (*n*).

One study from 1987 to 1990 comparing the accuracy of Iowa State University's yield goal N recommendation system to the EONR showed a poor relationship between the yield-based recommendation calculated based on actual yield and the

EONR calculated from the fitted N response curve (Blackmer et al., 1992). The *r*² value for the relationship between the yield-based N recommendation and EONR was 0.21 for 25 trials of corn after corn and 0.06 for 25 trials of corn after soybean at the same locations. The average post-hoc EONRs were lower than the yield-based recommendations by 43 kg N ha⁻¹ for corn after corn and 85 kg N ha⁻¹ for corn after soybean. The individual field EONRs varied from 0 to 251 kg N ha⁻¹ for corn after corn and from 0 to 197 kg N ha⁻¹ for corn after soybean. In corn after corn there were only four trials with yield goal recommendations within 10 kg ha⁻¹ of the EONR, and in corn after soybean all the yield goal recommendations overestimated the EONR with only four trials within 10 kg ha⁻¹ greater than the EONR. This suggests that the simplest yield-goal based N recommendation (Eq. [7]) should be adjusted for all sources of N and efficiencies of their use (Eq. [11]) specific to each individual corn field, but the data to make those adjustments are unavailable in most situations.

There was one post-hoc comparison of several yield-based recommendation systems and N needs predicted by the Maize-N model (Setiyono et al., 2011). The root mean square error for observed and simulated EONRs for 11 experiments conducted in Nebraska and South Dakota were 41, 48, 33, and 61 kg N ha⁻¹ using recommendations from Nebraska, Kansas, South Dakota, and Missouri, respectively. The authors noted that statewide recommendations for border regions of large states with substantial rainfall gradients may not predict N rates as well as for the bulk of the state. This is an inherent problem with recommendations based on empirical data: it is expensive and time consuming to obtain sufficient data over many years for accurate prediction of N rates for all conditions. Several other shortcomings of yield-based recommendations are enumerated below in the MRTN section.

Strengths of Yield Goal Recommendations

The primary strengths of the yield goal system of making N recommendations are it is perceived as "logical" by farmers and farm advisors that N fertilizer rates should match in some way

Table 1. Selected N credits for annual legumes in yield-based N recommendations.

State	Annual legume(s)	N credit kg ha ⁻¹	Reference
Georgia	Soybean, peanut	22–45	University of Georgia, 2008
Kansas	Soybean	45	Leikam et al., 2003
North Dakota	Soybean	45	Franzen, 2010
Nebraska	Soybean–sandy soil	39†	Shapiro et al., 2008
	Soybean–medium to fine texture soil	50†	
	Dry bean	28	
Oregon	Bean, pea	56	Gardner et al., 2000
Pennsylvania	Soybean	‡	Beegle, 2015
South Carolina	Soybean	22–34	Clemson University, 2007
South Dakota	Soybean	45	Reitsma et al., 2008
Virginia	Soybean	§	Alley et al., 2009
	Peanut	50	
Vermont	Soybean, dry bean, pea	34	Jokela et al., 2004
Wyoming	Bean	34	Blaylock et al., 1996

† If soybean yield <2000 kg ha⁻¹ (30 bu acre⁻¹) then N credit is 1.67 kg N (kg soybean grain)⁻¹ (1.0 lb N bu⁻¹).

‡ Nitrogen credit based on yield of previous soybean crop at 1.67 kg N (kg soybean grain)⁻¹ (1.0 lb N bu⁻¹).

§ Nitrogen credit based on yield of previous soybean crop at 0.83 kg N (kg soybean grain)⁻¹ (0.5 lb N bu⁻¹).

Table 2. Selected N credit for first-year corn grown after alfalfa based on level of stand and other factors.

State	Condition	Level of stand				Reference
		H†	M	L	VL	
		Nitrogen credit				
		kg ha ⁻¹				
Georgia	Post-bloom	90–112	–	–	–	University of Georgia, 2008
Iowa	None noted	0–34‡				Sawyer, 2016
Kansas	Tillage§	134¶	90	45	0	Leikam et al., 2003
New York	Sod	185#	155	123	93	Ketterings et al., 2003
North Dakota	Harvested	168††	112	56	0	Franzen, 2010
Nebraska	Sandy soil	112‡‡	78	45	–	Shapiro et al., 2008
	Medium & fine textured soil	168‡‡	134	101	–	
Pennsylvania	Low prod. fields	90§§	67	45	–	Beegle, 2015
	Med. prod. fields	123§§	78	45	–	
	High prod. fields	134§§	90	45	–	
South Dakota	Tillage§	168¶	112	56	0	Reitsma et al., 2008
Utah	None noted	112¶¶	56	28	–	Topper et al., 2010
Virginia	None noted	101##	78	56	–	Alley et al., 2009
Vermont	None noted	134†††	90	–	–	Jokela et al., 2004
Wisconsin	Sandy soil	112‡‡‡	78	45		Bundy et al., 1997
	Medium & fine textured soil	168	134	101		
Wyoming	Stubble only	0.90 kg N × % alfalfa in stand/acre				Blaylock et al., 1996
	Stubble plus >2240 kg ha ⁻¹ of tops	1.34 kg N × % alfalfa in stand/acre				

† High indicates 100% stand unless noted otherwise.

‡ Range of rates to apply; not a credit.

§ Reduce N credit by 50% if no-till production.

¶ H, M, L, and VL are excellent (>54 plants m⁻²), good (54–22 plants m⁻²), fair (22–11 plants m⁻²), and poor (<11 plants m⁻²).

H, M, L, and VL are >50, 50 to 26, 25 to 1, and 0% alfalfa in stand.

†† H, M, L, and VL are >54, 43 to 32, 22 to 11, and <11 plants m⁻².‡‡ H, M, and L are >43, 43 to 16, and <16 plants m⁻².

§§ H, M, and L are >50, 49 to 25, and <25% alfalfa in stand.

¶¶ H, M, and L are 100, 90 to 71, and 70 to 31% alfalfa in stand.

H, M, and L are 75 to 50% stand (good, >8960 kg ha⁻¹), 49–25% stand (fair, 6720–8960 kg ha⁻¹), and <25% stand (poor, <6720 kg ha⁻¹).

††† H and M are >60 and 60 to 20% legume in stand.

‡‡‡ H, M, and L are >70, 30 to 70, and <30% alfalfa in stand.

expected grain yield, it has been utilized for more than 50 yr with what is perceived by farmers and farm advisors as a system without large shortcomings, and it is easy to implement in its simplest form ($N_f = n(Y_{GOAL} - N \text{ credits})$). This approach is most likely to be successful in environments where year-to-year differences in grain yield, N mineralization, and N losses are minimal—perhaps arid environments where soil moisture is managed by irrigation.

Limitations of Yield Goal Recommendations

Logic is sometimes referred to as “a systematic method of coming to the wrong conclusion with confidence” (perhaps Edward A. Murphy). The primary limitations of the yield goal N recommendation system are the uncertainties at the time of fertilization of predicting the yield, internal N efficiency, soil N mineralization, and soil and fertilizer use efficiency that will arise from the interaction of maize hybrid, cropping system management, weather, landscape, and soil biological, chemical, and physical properties. Seasonal and within-field variation in yield and N loss is likely to be high in humid environments, particularly in landscapes containing excessively well-drained and/or poorly drained soils, making prediction of N fertilizer needs most difficult under these conditions. Dynamic modeling of crop and soil processes at the landscape level affecting

yield, efficiency, and N transformations and loss, as well as improved weather prediction, may lead to substantially better yield-goal based N recommendations compared with the static and simplified yield-goal based systems currently practiced.

Maximum Return to Nitrogen Recommendation System

Nitrogen rate guidelines for corn calculated by the MRTN system were developed using data from recent N rate response trials. The MRTN name reflects the fact that this system calculates the maximum (economic) return to nitrogen fertilizer (RTN). While fertilizer rate recommendations based on response trials and economic return is not a new concept (Johnson, 1953; Heady and Pesek, 1954), emphasis on maximum return and adjustment for varying N and corn prices disappeared as implementation of the yield-goal system relating N fertilization requirement to attainable yield became popular. Also, adjustment for N/corn grain price ratio can improve rate recommendations (Kim et al., 2013).

An alternative rationale for corn N recommendations was implemented in Wisconsin based on the grouping of yield response data from N rate trials according to soil-specific characteristics (Vanotti and Bundy 1994a, 1994b). This alternative rationale portended the development of the MRTN approach. Additional impetus

to replace the yield-based approach was provided by results from numerous N response trials during the latter decades of the 20th century where corn yield increased faster than the per-bushel fertilizer N requirement (Sawyer et al., 2006; Woli et al., 2016).

The Maximum Return to Nitrogen Approach

Development of the MRTN approach occurred because of several important concerns about N application rates for corn production in the Midwest Corn Belt. These included: (i) recommendations differing across states, with some using yield-goal and others using various systems such as soil-test based or soil yield potential; (ii) yield-based rates were often higher than observed optimum rates in research at high yield levels; (iii) yield-based rates were lower than observed optimum rates for less-productive soils; (iv) lack of relationship between the EONR and grain yield at EONR (Fig. 6); (v) high and variable N prices; and (vi) cross-state agency programs, crop advisors, and producers desiring uniform recommendations across state boundaries. Of most importance was the poor correlation between yield-goal-based rate recommendations and optimal rates found in research trials; long-term research from the 1970s to the 1990s indicated that optimal N rates had not changed despite yield increases (Sawyer et al., 2006); and yield level was found to be unrelated to EONR (Vanotti and Bundy, 1994a, 1994b; Lory and Scharf, 2003; Scharf et al., 2006a).

The goal of the MRTN development was to have the same approach to N rate recommendations for corn across the Midwest Corn Belt, making use of N response data from each state or a specified region within the state. This was expected to result in different N rates across the Corn Belt. Other important aspects in the development of this regional approach were to better understand corn response to N application rate; to create a system to estimate the most profitable N rate; to recognize risks associated with selection of a N rate; and to provide the end-user with a method for making N rate decisions based on economic inputs (current prices for grain and fertilizer N) and their tolerance for risk.

The MRTN approach was developed over a 2-yr period. Initial discussions took place in 2004 and N response data was compiled into a database in 2005. The online Corn N Rate Calculator (<http://cnrc.agron.iastate.edu/>) was developed in 2005 and a regional extension publication was published in

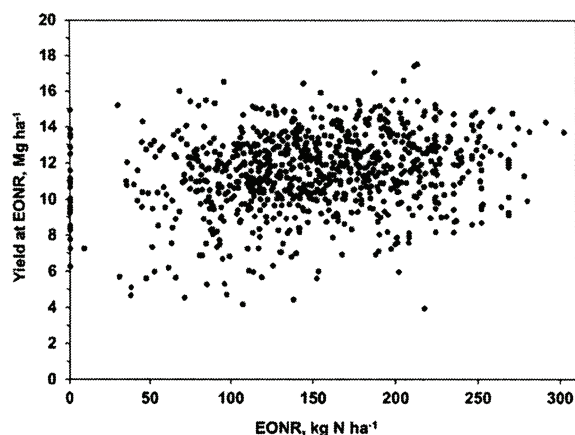


Fig. 6. Relationship between the economic optimum nitrogen rate (EONR) and corn yield at the EONR from the seven-state corn after soybean maximum return to nitrogen (MRTN) database (linear $R^2 = 0.05$, $p < 0.001$).

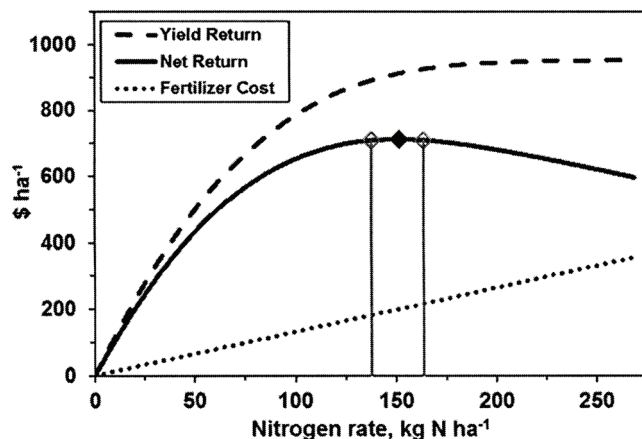


Fig. 7. Fertilizer cost, yield return, and net return to nitrogen (RTN) for the Iowa corn after soybean maximum return to nitrogen (MRTN) database (198 N response trial sites), with N at $\$1.32 \text{ kg}^{-1} \text{ N}$ ($\$0.60 \text{ lb}^{-1} \text{ N}$) and corn at $\$0.24 \text{ kg}^{-1}$ ($\$6.00 \text{ bu}^{-1}$). The center symbol on the net RTN line corresponds to the MRTN rate and the two symbols with the vertical lines indicate the rate within $\$2.47 \text{ ha}^{-1}$ ($\$1.00 \text{ acre}^{-1}$) of the MRTN.

2006 (Sawyer et al., 2006). Currently, seven states use the Corn N Rate Calculator, representing 59% of the corn grain production in the United States (National Corn Growers Association, 2017).

Details of the MRTN approach are described in Nafziger et al. (2004), Sawyer and Nafziger (2005), and Sawyer et al. (2006). Briefly, best fit response functions—linear, linear+plateau, quadratic, or quadratic+plateau as determined by research personnel in each state—are assigned to each individual N response trial data resulting in a dataset of site response functions. Return to N is calculated based on these functions for N rates ranging from 0 to 269 kg N ha^{-1} (0–240 lb N acre^{-1}) in $1.12 \text{ kg N ha}^{-1}$ (1 lb N acre^{-1}) increments. Gross return is ΔY (estimated yield at each N rate minus yield at $N = 0$) \times price of corn grain. Return to N is calculated by subtracting cost of N (N rate \times price of N) from the gross return. This calculation is done for all response trials in the database. The overall RTN for selected trial subsets is the average RTN across trials at each N rate. The RTN curve is asymmetrical (Fig. 7), with the MRTN being the N rate with the maximum overall RTN where the slope of the curve is zero. The overall RTN is used to determine endpoints for a range of N rates that produce profitability similar to the MRTN; default is within $\text{US}\$2.47 \text{ ha}^{-1}$ ($\text{US}\$1 \text{ acre}^{-1}$) of the maximum (Fig. 7). Gross return, cost of N, and RTN curves along with the range of profitable N rates are displayed on the MRTN website (Fig. 7) based on user choice of region, rotation, and prices of N and corn.

Uniqueness of the Maximum Return to Nitrogen Approach

There are several key aspects of the approach that make it a unique utilization of N response trials and implementation of an economic analysis. These aspects include: use of regression models for each N response trial; use of a large response trial database; and calculation of net RTN across a range of N rates for each response trial, with determination of the average RTN-maximizing N rate across specific groupings of response trials. An important feature of the MRTN approach is the use of fitted regression models to calculate RTN, and then averaging net returns across sites. This provides uniformity of economic

return data across a range of N rates, for example from 0 to 269 kg N ha⁻¹ (0–240 lb N acre⁻¹), and simplifies use of data from N rate trials that do not have the same rates or increments.

Specific criteria are used for inclusion of site response trials into the database. Sites must include three to four replications of small plot or field strip trials where five to seven N rates, including a zero or near zero N rate, were applied and N was managed well (majority are spring-applied N). If the previous criteria were met then the following information for each site was entered in the database: corn grain yield response regression model parameters, maximum N rate applied, N rate increments, agronomic maximum yield and associated N rate calculated from the N response model, trial location, year, small plot or field strip, soil series, previous three crops, number of years with same N rates, manure history, soil yield potential, tillage system, and parent material. Trial database development and yearly maintenance are the responsibility of each state.

An important assumption in the MRTN approach is that regression equations represent the response of yield across N rates at each site, and thus are best sources for economic return calculations. In addition, use of regression model databases allows for direct insertion of new N response trial data and calculation across any desired grouping of trials. For example, as new response trials are conducted and results converted to regression models, the database can be updated. As of 2016 there are 1674 trials from seven states in the overall database: Illinois (696), Indiana (150), Iowa (371), Michigan (56), Minnesota (147), Ohio (116), and Wisconsin (138). There is no minimum number of trials required, but the trials need to adequately represent the crop rotation, soil or geographic region, or other grouping for which an N recommendation will be calculated. The database allows a direct use of recent research, documents research utilized in the N rate recommendations, and keeps recommendations up to date with changing climatic conditions, corn hybrids, and crop production practices.

Response trials in the database can be grouped based on different criteria. The most common grouping is previous crop such as corn after corn and corn after soybean. The “soybean credit” in the MRTN approach is measured empirically rather than assumed, and that differences in magnitude across states and regions represents an improvement. Grouping response trials allows for direct use of response trial information in development of specific recommendations. In some states, trials are additionally grouped based on geographic locations within the state (Iowa, Illinois), soils (Wisconsin), or geographic location and soils (Indiana). These groupings allow for more specific recommendations. During development of the MRTN, response data from multiple states were used to investigate other potential groupings; such as yield level, tillage, etc. (Sawyer and Nafziger, 2005; Sawyer et al., 2006). That analysis did not reveal substantial or consistent differences in MRTN for those factors or across a range of corn yields from less than 9.4 Mg ha⁻¹ (150 bu acre⁻¹), 9.4 to 12.5 Mg ha⁻¹ (150–200 bu acre⁻¹), and greater than 12.5 Mg ha⁻¹ (200 bu acre⁻¹). Also, N rate and net return from the MRTN approach was evaluated against the yield-based system, with the MRTN producing lower mean N rate and greater net return (Sawyer and Nafziger, 2010). These results validated the decision to use yield response instead of yield in

the MRTN. In addition to rotations such as continuous corn and corn after soybean, the MRTN approach could be used for corn in any rotation as long as an adequate number of N response trials is available to represent corn response to N rate.

Maximum Return to Nitrogen Guidelines

The MRTN calculation allows investigation of RTN across a wide range of N rates and economic inputs (Fig. 7–8). As shown in Fig. 7 (an example for corn after soybean in Iowa with output from the online Corn N Rate Calculator), the net RTN output produces a classic flat payoff function (Hutton and Thorne, 1955; Jardine, 1975; Pannell, 2004; Archer, 2005). While there is a peak in the RTN (the MRTN), the RTN is relatively flat across a range of N rates (Fig. 7). This flat response was recognized and previously incorporated into N rate guidelines for Iowa corn production (Voss and Shrader, 1979), with suggested rate ranges for corn after soybean of 112 to 168 kg N ha⁻¹ (100–150 lb N acre⁻¹) and for corn after corn 168 to 224 kg N ha⁻¹ (150–200 lb N acre⁻¹). Therefore, prediction of an exact optimal N rate has inherent uncertainty, and in the MRTN approach a profitable range is used within \$2.47 ha⁻¹ (\$1.00 acre⁻¹) for the default setting. This range indicates some of the uncertainty in recommended N rates, and allows producers a range of rates to choose from with the expectation of similar net return. The MRTN rate is at the peak of the RTN curve, and that rate minimizes economic errors caused by the choice of a rate, that is, errors from under-application and over-application are minimized at the MRTN rate.

Yield is nearly maximized within the profitable range calculated from a MRTN database (Fig. 8). This means that applying N rates greater than the MRTN rate could result in a small yield increase but a decrease in RTN. The RTN response is asymmetrical, dropping off faster as rate is lowered than as rate is increased. That is, the risk of loss in net return is greater with below-optimal N rates than with above-optimal rates, an effect well known by producers.

The MRTN approach allows direct comparison of varying N/corn price ratios (Fig. 9), and this information is a component of the online Corn N Rate Calculator. Increasing N

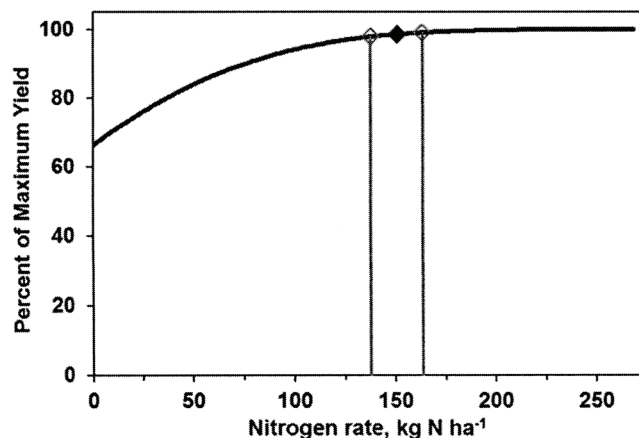


Fig. 8. Percent of maximum yield across N rates for the Iowa corn after soybean MRTN database, with N at \$1.32 kg⁻¹ N (\$0.60 lb⁻¹ N) and corn at \$0.24 kg⁻¹ (\$6.00 bu⁻¹). The center symbol indicates the MRTN rate and the two symbols with the vertical lines indicate the rate within \$2.47 ha⁻¹ (\$1.00 acre⁻¹) of the MRTN.

prices relative to corn grain price (increasing ratio) lowers the MRTN. As corn and N price both increase, but the same price ratio is maintained, the MRTN rate does not change but the profitable range narrows. This reflects greater risk in N rate decisions at high prices. With rapidly fluctuating N and corn prices, this economic comparison allows producers an opportunity to observe the effects on rate decisions. The MRTN approach provides a range of rates at user-prescribed prices that provide maximum profitable return and allow adjustment for other factors such as enterprise capital allocation, risk tolerance, water and air quality, information sources such as local research or plant and soil tests, and other crop rotation adjustments such as legume cover crops.

Since the MRTN database includes site response trials and associated regression models, several aspects of the MRTN output can be queried to assist producers when deciding on N rates to apply: percent chance of achieving a certain relative yield, percent chance of N sufficiency, frequency of over- and under-application, net loss or gain from over- and under-application, chance of negative or positive RTN with over- and under-application, and potential gain from site-year rate adjustment. For example, to help producers understand risk associated with N rate, especially over- or under-application, the expected average RTN at a rate higher or lower than the MRTN rate and the associated chance of a positive or negative return can be calculated. For the trials in the database for corn after soybean in Iowa, with prices at \$1.32 kg⁻¹ (\$0.60 lb⁻¹ N) and \$236 Mg⁻¹ (\$6.00 bu⁻¹) corn, the MRTN is 151 kg N ha⁻¹ (135 lb N acre⁻¹). At 56 kg N ha⁻¹ (50 lb N acre⁻¹) greater than the MRTN rate (207 kg N ha⁻¹; 185 lb N acre⁻¹), there is an 85% chance of having a net return less than at the MRTN rate, and on average, this translates to a loss of \$63.77 ha⁻¹ (\$25.78 acre⁻¹). At 56 kg N ha⁻¹ (50 lb N acre⁻¹) less than the MRTN (95 kg N ha⁻¹; 85 lb N acre⁻¹), there is a 60% chance of having a net return less than at the MRTN rate, and on average a loss of \$144.47 ha⁻¹ (\$58.49 acre⁻¹).

Strengths of Maximum Return to Nitrogen

A main strength of the MRTN is that it creates N rate guidelines directly from the N response trial database. It is easy to add new response data, or take out old data, which keeps the guidelines current. The database provides information for the dynamic online Corn N Rate Calculator and documents the data used for current rate guidelines. Using regression models for the individual N response trial sites allows use of trials with different N rates and allows for many MRTN calculations and other queries as described above. The response trial database inherently incorporates temporal and spatial variability among fields because the trial results are from many locations and years, which is useful for understanding recommendation uncertainty. Having a response database of many trials helps remove potential response prediction errors that might occur with small datasets. Ultimately, the research trial database provides information needed for N rate prediction into growing seasons with unknown rate requirement.

The MRTN approach is based on economic profitability from N use, which is derived from yield response and is what pays for N fertilization. The MRTN approach was developed for corn, but can be used for any crop that requires N fertilization, and can be used for crops in various rotations. Currently,

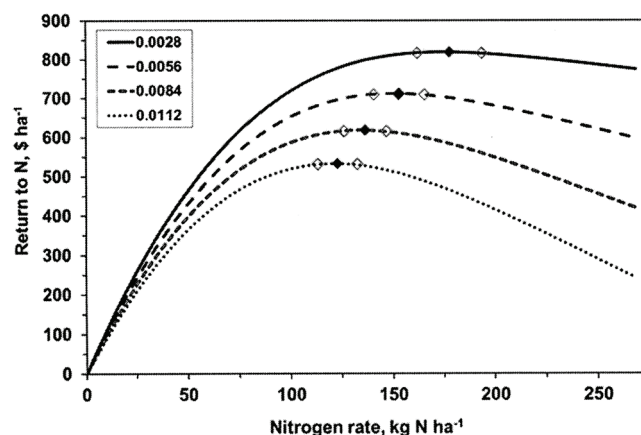


Fig. 9. Comparison of net return to nitrogen (RTN) for the Iowa corn after soybean maximum return to nitrogen (MRTN) database, with corn at \$0.24 kg⁻¹ (\$6.00 bu⁻¹) and N at \$0.66, \$1.32, \$1.98, and \$2.64 kg⁻¹ (\$0.30, \$0.60, \$0.90, and \$1.20 bu⁻¹) or N/corn grain price ratios of 0.0028, 0.0056, 0.0084, and 0.0112 (0.05, 0.10, 0.15, 0.20). The symbols on each net RTN line correspond to the MRTN rate (solid symbol) and profitable range within \$2.47 ha⁻¹ (\$1.00 acre⁻¹) of the MRTN (open symbols).

the MRTN approach is also used for N rate guidelines for wheat (*Triticum aestivum* L.) in Illinois, Wisconsin, and North Dakota. The MRTN can be used for any quantitative crop response input, including such things as seeding rate. The approach also allows for integration of response trials across state boundaries, and therefore, has the potential for cross-state guidelines.

The MRTN approach provides opportunity for user input and N rate adjustment, such as geographic location, previous crop, and N fertilizer (or other N inputs such as manure) and corn prices. In contrast to most yield-based systems, the MRTN approach utilizes separate databases for corn after corn and corn after soybean, thus avoiding the need to assume the value of a “soybean N credit.” The system provides a suggested N rate at the MRTN, but also provides a profitable range that can be used by producers to adjust rates based on experience, N input source, attitude toward risk, available capital, water and air quality concerns, local information, and expectation of climatic conditions that may influence N response. The MRTN rate guidelines could incorporate environmental N costs (water and air systems), such as by applying higher costs to N in excess of the EONR for individual trials or direct costs based on a per unit of nitrate N lost if the N rate dependence effects were available.

Limitations of Maximum Return to Nitrogen

The MRTN approach has some of the same limitations as other recommendation systems. There is large variability in temporal and spatial N response, which increases the most profitable RTN range and lowers certainty of getting the “correct” N rate in a given field in a given year. The approach incorporates variability into the N recommendation through use of response models, but does not solve the problem of how to create site-specific (by field or subfield) N fertilization guidelines or directly provide adjustment for seasonal factors influencing N response. While the MRTN approach does not provide the exact N rate needed for individual fields due to information noted previously, it does provide a high level of confidence that high yields (percent of maximum yield in Fig. 10) will be achieved at the MRTN rate for the majority of fields. While spatial and temporal variability

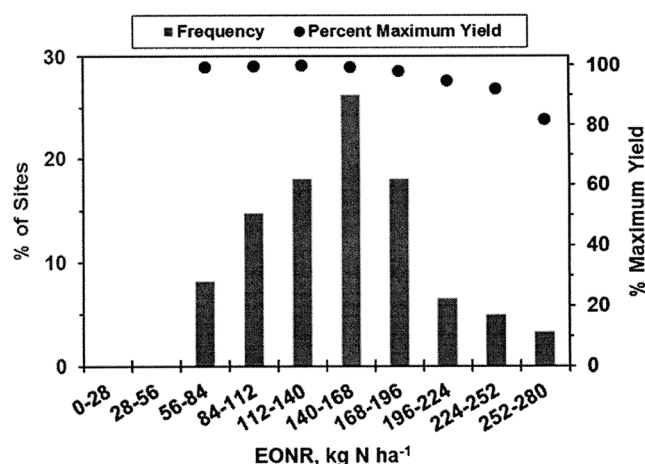


Fig. 10. The economic optimum nitrogen rate (EONR) frequency distribution for the northern Illinois corn after soybean response trials and the associated percent of maximum yield within each frequency range if fertilized at the maximum return to nitrogen (MRTN) rate 164 kg N ha⁻¹ (146 lb N acre⁻¹) rather than actual EONR rate for each site.

in EONR is widely recognized, there currently is no reliable method to incorporate such variability into field-specific rate guidelines, although computer software models discussed below are attempting to address this spatial and temporal variability in EONR. The use of yield level in the recommendation process does not resolve the problem (Fig. 6).

Not using yield goal in the MRTN system is seen as a drawback by farmers and applied agronomists, and the idea that “more yield requires more fertilizer” remains strong. This idea has an intuitive appeal, but the concept of BBC of soils indicates that N fertilizer recommendations should not be expected to increase linearly with an increase in yield. The MRTN approach does not use yield level, which means that producer management (as it is perceived to affect yield) does not directly influence N rate. The N response data in the MRTN database clearly show that correlation between yield level and MRTN over a set of trials is poor (Fig. 6), and this has been shown by others (Blackmer et al., 1992; Lory and Scharf, 2003), and supports the use of yield response rather than yield level in the MRTN approach.

While not directly a limitation of the approach itself, the MRTN requires a database that adequately represents N response (and for desired data subsets) for effective implementation. The number of trials currently varies by state and subsets across the states implementing the MRTN approach. Additional research could aid in procedures for determining needed or optimal number of response trials. In addition, continual research is needed to provide updated response trials.

Future Maximum Return to Nitrogen Enhancement

The MRTN response trial database could be used to better incorporate N adequacy risk management into rate recommendations. This would aid producers in the choice of specific rates. Analysis of the data in terms of response probability would help infuse risk management into N rate guidelines. In addition, it might be possible to apply an over-application or environmental penalty relative to N rates greater than the optimum RTN.

One aspect of the regional MRTN approach that has potential, but has not yet been accomplished, is development of cross-state guidelines based on commonality of soil and climatic conditions rather than on political boundaries. To date, inadequacy of response trial databases or dissimilarity of responses have not justified cross-state guidelines. A research effort with trials conducted at the same time and with reasonably similar methodology would aid the development of such regional guidelines. In addition, questions arise about use of metadata to aid in development of guideline subgroups, such as soils, watersheds, or substate regions. Given that efforts to produce cross-state or field-specific guidelines based on the large MRTN database have so far been unsuccessful, development of such guidelines will require a large research effort within and among states.

Soil Tests for Nitrogen Recommendations for Corn

Soil Nitrogen Supply Potential

Residual inorganic soil N from fertilizer or manure and N mineralized from SOM have been shown to meet a substantial portion of crop N needs (Roth and Fox, 1990; Sawyer et al., 2006; Meisinger et al., 2008). Estimates of the soil N supplied by residual inorganic N have been the most successful soil N tests, particularly in subhumid and semiarid regions as shown by the long history of residual nitrate tests in the western U.S. United States (Dahnke and Vasey, 1973; Schepers et al., 1986).

Estimates of soil N supplied by SOM mineralization, however, have been problematic and are often not explicitly included in yield-based or the MRTN recommendation systems, or are only included as broad general estimates. The reason for this is that few field or laboratory tests to measure N supplied by SOM have proven sufficiently reliable to be explicitly included in N recommendation systems. A comprehensive review of N availability tests showed a long history of the failure of most laboratory and field tests to accurately predict soil N supply (Griffin, 2008). Two tables in this comprehensive review provide references to 11 N availability tests evaluated using net mineralization of SOM during aerobic incubations in the laboratory, and 12 tests evaluated in field trials, but only one of the tests, the Illinois soil N test, was proven sufficiently reliable for guiding N recommendations. Papers published after this review, however, show mixed results for the Illinois soil N test (see below). More recently a combination of CO₂ evolution from a rewetted soil combined with water extractable organic N and C has been proposed as a method to improve N recommendations based on preliminary field trials in Texas (Harmel and Haney, 2013; Franzluebbers, 2016), but much more testing will be required for this method to demonstrate reliability across many environments and management practices (Sullivan and Granatstein, 2015).

The N supply from SOM can have a large influence on the optimum fertilizer N rate for any given field and if soil N supply potential is not adequately estimated the resulting recommendations are likely to result in over- or under-fertilization. Soil N supply may be accounted for explicitly by using source terms measured with soil testing, indirectly by grouping soils and/or management systems that have similar fertilizer N response curves, or implicitly by using within-field reference strips. An explicit estimate of soil N supply provided by soil testing may include both residual-N and/or mineralizable organic N.

Pre-Season or In-Season Adjustments Based on Soil Nitrogen Testing

Initial approaches used to determine the soil's plant available N supply included the pre-plant nitrate test and the pre-sidedress nitrate test. More recently the Illinois soil N test has been evaluated for its potential to guide adjustments in N recommendations and specifically to identify fields where soil N supply is sufficient to eliminate further N applications that year (Khan et al., 2001). Independent of the actual chemical or biological test, the effectiveness of any test used to accurately adjust a base N recommendation depends on replicated calibration and validation trials with multiple N rates across the area for which the recommendation system is being developed. Some soil N tests gained nationwide adoption, others regional adoption. The advantages and disadvantages of each of the three main N tests are discussed below.

Pre-Plant Nitrate Test

The pre-plant nitrate test is most commonly recommended for use in dry regions with deep soils where leaching and/or denitrification losses are minimal (Bundy and Meisinger, 1994; Hergert, 1987). Most pre-plant nitrate test guidelines require soil to be sampled in early spring to a depth of 60 to 120 cm or the effective rooting depth if root-limiting layers are present (Bundy and Meisinger, 1994; Shapiro et al., 2003). In such environments, the recovery efficiency of residual inorganic N in the root zone is expected to be equivalent to that of fertilizer N so the nitrate content of the sample is typically subtracted directly from the baseline N recommendation (Brown et al.,

2010; Davis and Westfall, 2009; Shapiro et al., 2008). Some states, such as Wisconsin (Bundy et al., 1995) and Nebraska (Shapiro et al., 2008) suggest sampling in depth increments to provide additional information about distribution of the nitrate with depth.

The pre-plant nitrate test typically assesses residual carryover fertilizer N. Fall sampling is sometimes suggested if nitrate leaching or denitrification between sampling and planting of the succeeding crop is minimal or nonexistent. However, in most cases spring sampling immediately before seeding is recommended because spring sampling includes the effects of nitrate leaching and denitrification losses during the winter. In humid climates the pre-plant nitrate test is typically less meaningful as snow melts and early season rainfall increase the potential for leaching and denitrification losses of residual soil nitrate between sampling time and seeding of the next crop (Fig. 11). However, in both humid and dry conditions, the pre-plant nitrate test can capture some nitrate from spring mineralization in fields with long-term histories of manure application (Roth and Fox, 1990).

In semiarid regions such as Nebraska, South Dakota, and North Dakota where the pre-plant nitrate test is most useful, its adoption may be limited by the effort required to collect meaningful soil samples. The 60 cm or greater sampling depth required for the pre-plant nitrate test makes it a difficult and time-consuming sample to collect. In addition, spatial variability of profile soil nitrate, which is exacerbated by banded fertilizer N as it is for all banded nutrients, requires that a large number of subsamples are collected to form a composite sample that

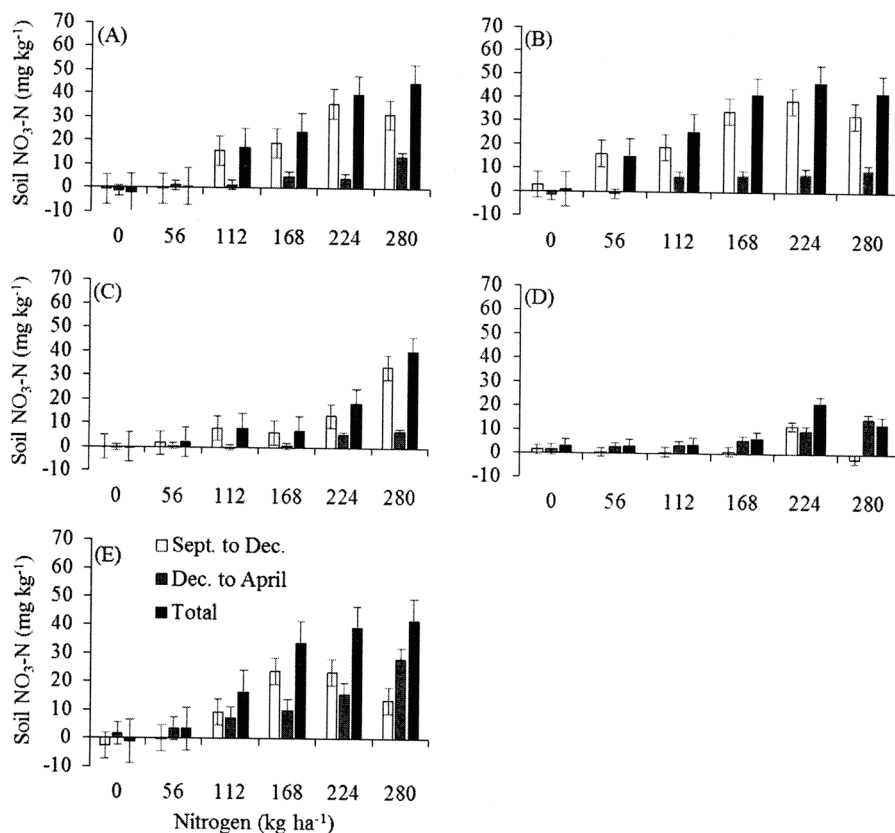


Fig. 11. Soil nitrate loss from September (silage harvest time) to December (end-of-season) and from December to April (next spring). Total nitrate N loss is sum of nitrate N losses from September to December and December to April. A: 2001; B: 2002; C: 2003; D: 2004; and E: 2005. (Sadeghpour, et al., 2017).

accurately reflects the average nitrate concentration within a field or management unit (Reuss et al., 1977; Starr et al., 1992). For example, a summary of the spatial sampling intensity by Bundy and Meisinger (1994) suggested that 20 cores per field management unit were needed to estimate the mean nitrate N content to within 15% in about 8 out of 10 management units.

Pre-Sidedress Nitrate Test

The pre-sidedress nitrate test was created by Magdoff et al. (1984) as an in-season soil N assay to make or adjust a sidedress N recommendation in soils where organic N mineralization, primarily from manure applications, is expected to meet a substantial portion of crop N needs. In Iowa, the test is referred to as the late spring soil nitrate test (LSNT) (Blackmer et al., 1989; Binford et al., 1992a) because the test was calibrated by application of N fertilizer rates to fields with no manure history. The test requires collection of a soil sample from the surface 30-cm layer of soil when corn is 15- to 30-cm tall and soil processing and analysis that can be completed in 48 h.

The approach originally outlined by Magdoff et al. (1984) was based on Stanford (1973) to develop an N recommendation from the expected yield (Y_{GOAL}), soil nitrate concentrations, Q_{NO_3} , n , and RE_N . Subsequent papers directly calculated a critical concentration of soil nitrate from the relationship of relative yield with soil nitrate concentrations (Blackmer et al., 1989; Fox et al., 1989; Cela et al., 2013).

The pre-sidedress nitrate test has proven useful for improving fertilizer N recommendations in the humid eastern United States for corn grown on land receiving manure, and where legumes have been grown in the rotation (Andraski and Bundy, 2002; Evanylo and Alley, 1997; Meisinger et al., 1992a; Roth et al., 1992; Sims et al., 1995). In most states, the maximum amount of pre-plant N fertilizer recommended where the pre-sidedress nitrate test will be used is 22 to 34 kg N ha⁻¹. Interpretations of the pre-sidedress nitrate test vary from state to state but generally support the recommendation of no sidedress N if soil nitrate concentrations exceed 20 to 25 mg kg⁻¹ NO₃-N.

An advantage of the test is that it provides a recommendation for sidedressed N after soil and weather factors have influenced soil nitrate concentrations up until immediately before the time of sidedressing. This is also a practical difficulty with the test. For example, many dairy farmers grow corn and forage crops, and typically pre-sidedress nitrate test samples will need to be taken during a busy first-cut harvest window of the forage crops on these farms (Magdoff et al., 1990). In addition, collecting the soil samples in some environments is not easy, rendering the test unpopular in parts of the United States, such as in New England where stony soils are abundant. A third reason why the pre-sidedress nitrate test is not widely used relates to its unreliability due to rainfall near the time of sampling, which can cause leaching or denitrification of nitrate mineralized from organic sources. If rainfall occurs shortly before sampling, underestimation of the nitrate supplying capacity of the soil and overfertilization is likely; if rainfall occurs shortly after sampling and the nitrate concentration is greater than the critical concentration, underfertilization is likely. In addition, the pre-sidedress nitrate test also carries the large inherent spatial variability problem noted above for the pre-plant nitrate test.

Illinois Soil Nitrogen Test

The Illinois soil N test was developed as a routine soil analysis by Khan et al. (2001) to estimate hydrolyzable amino sugar-N that Mulvaney et al. (2001) had previously shown to be highly correlated ($r = 0.79$; $P < 0.001$) with check plot yield and fertilizer N response ($r = -0.82$; $P < 0.001$). Since its development, the Illinois soil N test has been evaluated by many researchers who have reported both successes in using the Illinois soil N test to differentiate N responsive from non-responsive sites (Khan et al., 2001; Klapwyk and Ketterings, 2006; Mulvaney et al., 2006; Sharifi et al., 2007; Williams et al., 2007a, 2007b) and failures (Barker et al., 2006; Laboski et al., 2008; Osterhaus et al., 2008).

Illinois soil N test results and optimum economic N rate or crop N uptake should not be expected to be linearly related across a diversity of soils, soil and crop management histories, and crop rotations because the Illinois soil N test does not determine soil nitrate. Thus, Illinois soil N test levels in soil samples collected when soil profiles contain significant amounts of nitrate N will not reflect the total amount of inorganic N available to the corn. This explained the lack of a yield response to N applications to first-year corn after alfalfa (*Medicago sativa* L.)/grass hay on soils testing low for the Illinois soil N (Lawrence et al., 2008) and the inability of the Illinois soil N test to capture manure N contributions mid-season (Klapwyk et al., 2006).

Strengths of Soil Nitrogen Tests

The need for inclusion of an accurate estimate of soil N supply potential, when developing a recommendation for a variety of soils and growing conditions, is well recognized among researchers and practitioners alike (Keeney, 1982; Stanford, 1982; Griffin, 2008). Under many management systems and in most environments, soil testing provides valuable information that can be used to reduce the uncertainty in estimated N fertilizer needs (Bundy and Malone, 1988; Andraski and Bundy, 2002). Inclusion of a soil testing approach in a recommendation system will typically reduce application rates, compared with approaches where N guidelines are based only on *estimated yield potential* or *maximum return to N*. Thus, inclusion of soil N test can enhance nutrient use efficiency, reduce N loss to the environment, and lead to savings in fertilizer costs.

Limitations of Soil Nitrogen Tests

What all chemical soil tests have in common is that they are, for practical reasons, limited to sampling at a specific time, depth, and density of sampling (cores per management unit). Thus, no soil testing process captures all currently available and potentially mineralizable organic N. Soil nitrate concentrations also can have high spatial variability across fields (Meisinger, 1984; Cambardella et al., 1994), which makes the collection of a representative sample challenging. In addition, a greater limitation of soil N tests is that all chemical soil tests ignore the soil–crop–weather interactions that determine the total amount of plant available N and its timing of release in relationship to crop N needs. We suggest that a more in-depth understanding of BBC, with its recognition of the importance of plant–soil–weather interactions, can help improve field testing of proposed soil N mineralization tests and thereby

improve N recommendations for corn. Nitrogen recommendations in irrigated systems, as shown in irrigated rice systems (Roberts et al., 2011, 2012), are more accurate and precise because predicting the N dynamics in the plant–soil–weather conditions of a field are less complex due to almost complete elimination of uncertainty caused by rainfall. Predicting the total amount of plant available N and its timing of release in relationship to crop needs over a growing season is substantially more difficult due to the interaction of rainfall with soil properties, soil management practices, and rotations. Additional sampling for soil nitrate may allow better estimation of soil N dynamics (Klapwyk and Ketterings, 2006) as illustrated by the corn–alfalfa rotation studies completed by Lawrence et al. (2008; 2009) in New York.

Plant Sensing and Plant Tissue Tests for Nitrogen Recommendations for Corn

Nitrogen performs a wide array of crucial functions in plants, and a less-than-adequate supply is reflected in a range of chemical and physical properties of those plants. Measurements of these properties by chemical methods or sensors can be used as a basis for making N rate recommendations or decisions.

Nitrogen decisions based on plant measurements have large advantages and disadvantages relative to other N decision systems for corn. The primary advantage is that plant measurements should provide a direct measure of N needs because: (i) The N uptake process is intrinsically part of the measurement rather than being external to it, (ii) N availability is gauged over a broader scale of time and space, and (iii) N availability is gauged later in the season and better accounts for the conditions of that season to date.

The disadvantage of making decisions based on plant measurements is that N management decisions based on plant measurements must be implemented during the season or in the next season. In-season N applications are becoming more common in the United States due to a string of wet springs in the Corn Belt that caused loss of pre-plant N fertilizer, N deficiency, and yield loss, but a substantial majority of corn producers still do not apply in-season N. Corn is a tall plant, making the logistics of in-season N application trickier than for other crops such as wheat and cotton (*Gossypium hirsutum* L.), which are routinely fertilized with N during the growing season. If N is to be applied with a tractor-based applicator, there is a

narrow window when plant-based diagnosis and N application must be accomplished. If high-clearance or aerial application of N is to be used, application expense or equipment availability may limit feasibility.

Evidence for improved accuracy estimating N needs with plant-based measurements is limited but suggestive. In 62 experiments across seven Midwestern states, Scharf et al. (2006b) found that Minolta chlorophyll meter measurements of leaf light transmission at various corn growth stages were much more strongly related to optimal N fertilizer rate ($r^2 = 0.53$ – 0.66 ; $P < 0.0001$ for all growth stages) than were results from a wide range of soil tests including the pre-side-dress nitrate test ($r^2 = 0.04$ – 0.23) (Fig. 12). Similarly, Scharf (2001) found that chlorophyll meter readings and whole-plant tissue N at stage V6 were related more strongly to optimal N rate ($r^2 = 0.41$ – 0.52) than was soil nitrate to the 30- or 60-cm depth at planting or sidedress timings ($r^2 = 0.18$ – 0.24). In another study Schmidt et al. (2011) found lower error in predicting N rate for corn using canopy reflectance measurements (average error 46 kg N ha⁻¹) compared with using the pre-sidedress nitrate test (average error 66 kg N ha⁻¹) or the Minolta chlorophyll meter (average error 72 kg N ha⁻¹). In some small data sets (Schmidt et al., 2009), there was no difference between soil and plant tests in the strength of their relationship with optimal N rate. Other evidence for improved accuracy estimating N needs is from Ma et al. (2005) who showed that reflectance and transmittance measurements of corn at the V6 stage were better indicators of N status than pre-sidedress nitrate test concentrations. Additional work testing the hypothesis that plant-based measurements of N status are more accurate than other tools is justified.

Sensing Spectral Properties for Nitrogen Recommendations for Corn

Nitrogen rates based on plant spectral properties are a recent development and offer great advantages of speed, exponentially larger sample size, and immediacy. Either reflectance or transmittance properties of leaves or canopies can be used, and reflectance properties can be measured either with proximal sensors or with sensors on aerial platforms, such as airplanes and satellites.

Proximal reflectance sensing has been most widely studied as a basis for N rate recommendations likely because this method

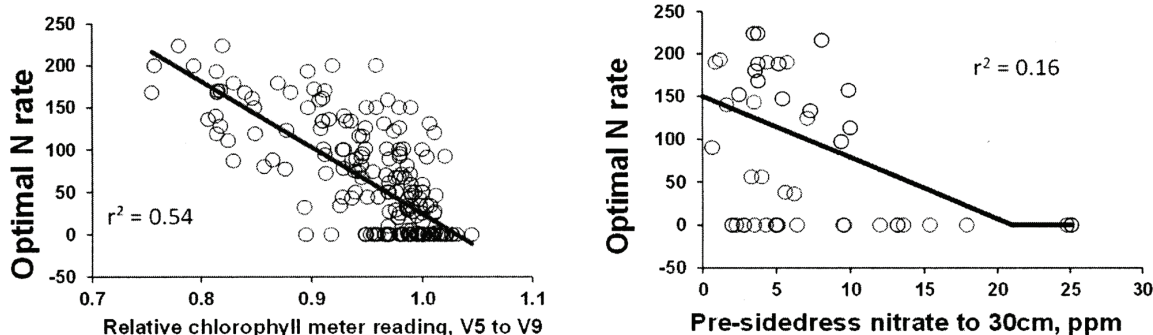


Fig. 12. Economically optimal N rate as a function of (1) relative chlorophyll meter readings of corn (V5–V9 growth stage), and (2) pre-sidedress soil nitrate N concentrations in the surface 30 cm of soil when corn is between the V4 and V6 stage of growth. Data are from 62 experiments in seven states (Illinois, Kansas, Michigan, Minnesota, Missouri, Nebraska, Wisconsin) published in Scharf et al. (2006b). The relative meter reading is the reading from an N-rate treatment divided by the reading for the high-N reference treatment.

has strengths that other plant-based approaches lack. The most commonly used proximal sensors are available from Trimble Navigation, Sunnyvale, CA (Greenseeker), and Ag Leader Technology, Ames, IA (OptRx). Proximal sensing can manage spatial variability in optimal N rates much more readily than hand-held transmission meters or physical samples collected for chemical analysis. Proximal sensors also do not delay fertilization with time required for transport and analysis of plant tissue (or soil) samples. Relative to remotely sensed reflectance properties, proximal sensors can operate in a much wider range of weather conditions.

Early studies on corn focused on the ability of reflectance measurements to distinguish N fertilizer rate treatments (Walburg et al., 1982; McMurtrey et al., 1994; Blackmer et al., 1994; Ma et al., 1996), with subsequent studies focused on the development of N rate recommendations (Bausch and Duke, 1996; Kitchen et al., 2010; Dellinger et al., 2008; Schmidt et al., 2009; Scharf and Lory, 2009; Tubaña et al., 2008; Bausch and Delgado, 2003; Solari et al., 2010). Most of the earlier studies were based on measurements of reflected sunlight, while most of the later studies are based on reflectance of pulsed light originating from the sensor. The latter are commonly referred to as “active sensors”.

The first system to make N rate decisions based on crop reflectance was developed by Bausch and Duke (1996). Their approach paralleled the decision system of Blackmer and Schepers (1995), which was based on chlorophyll meter measurements. In both systems, a small N application via irrigation water is triggered whenever relative reflectance/transmittance falls below 0.95 of the value observed in a non-N-limited reference area. This system has produced numerous positive outcomes (Bausch and Diker, 2001; Bausch and Delgado, 2003) but is limited in application to irrigated fields with the capability to add N to irrigation water. This limitation was removed by Varvel et al. (2007) by developing chlorophyll meter interpretations that produce a rate recommendation for a one-time application, which became the basis for the reflectance sensor interpretations developed by Solari et al. (2010).

The most widely published approach for developing N rate recommendations for corn has been to measure the EONR and reflectance across a range of environments, then regress EONR vs. reflectance (Kitchen et al., 2010; Dellinger et al., 2008; Schmidt et al., 2009; Scharf and Lory, 2009; Barker and Sawyer, 2010). This regression relationship can then be used to predict EONR in the future. In all cited studies, reflectance values were normalized compared with values from a reference treatment receiving a high N rate before, at, or shortly after planting. In studies where normalized and non-normalized reference values were compared, normalized values were always more strongly related to optimal N rates. This suggests that use of a high-N reference area will produce the most accurate N rate recommendations.

The need to establish and measure before fertilization a high-N reference area is a logistical obstacle that impedes the use of this method by farmers, and is a disadvantage of all approaches based on spectral properties. A “virtual reference area” proposed by Holland and Schepers (2013) might circumvent this obstacle if some of the corn in the field has sufficient N before fertilization (5% of the corn in Holland and Schepers,

2013), and can be identified from the sensor data stream using an automated algorithm. We are not aware of published data testing this assumption, or comparisons of this approach to use of a physical high-N reference. In measurements taken from an N rate response experiment, the mean value from the highest N rate appeared to be 11% lower than the “virtual reference” value (Holland and Schepers, 2013). If this occurred in a farm field, the whole field would receive a higher N rate (about 15 to 30 kg N ha⁻¹ depending on the recommendation system used) with the virtual reference than with the physical reference. In 16 farm fields in Missouri with physical high-N reference areas, the mean sensor value recorded in the reference area was as low as the 41st percentile of the whole field and as high as the 98th percentile (P. Scharf, unpublished data, 2016). This suggests that N rates based on virtual reference areas would often deviate substantially from N rates based on physical reference areas, no matter what percentile is chosen as sufficient.

Another approach to translate reflectance sensor measurements to N rate decisions was based on an N fertilization optimization algorithm, which is also known as the NFOA (Tubaña et al., 2008). This algorithm combines sensor-estimated yield potential, sensor-estimated yield response, and sensor coefficient of variation. A series of studies published over 8 yr (Lukina et al., 2001; Raun et al., 2001, 2002; Tubaña et al., 2008) documents the development of the N fertilization optimization algorithm, which was originally developed for winter wheat, and was modified by Tubaña et al. (2008) for corn.

Field-scale testing of sensor-derived N rates for corn has been minimal. Sensor-based N applications were tested at field scale by Scharf et al. (2011), who found that this approach saved 16 kg N ha⁻¹ and increased yield by 110 kg ha⁻¹ compared with N rates chosen by cooperating corn producers. These conclusions are based on 55 trials over 5 yr with an average of 5.6 replications per trial. The yield increase was observed mainly in one wet year of the 5-yr study.

Distance from sensor to target is a subject that deserves more study, especially when plants are small. Oliveira et al. (2013) found that sensor measurements were more reliably related to optimal N rate when taken from 50 cm above a cotton canopy than when taken from 25 or 100 cm above the canopy. At 100 cm, reflectance from the soil around small plants is likely to interfere with the ability of sensors to discern the N status of the plants.

A strength of reflectance-based N rate selection is the scale at which measurements are made because the approach automatically adapts to the scale of N variability in the field (within constraints imposed by the fertilization equipment) due to the reflectance being measured at the scale of individual plants. Other approaches to variable-rate application of N are generally zone- or grid-based, requiring assumptions or knowledge regarding the scale at which variability will occur.

Spatial variability in spectral properties of corn that has sufficient N remains an area where the accuracy of sensors to guide N rates can improve. Variations in soil moisture, soil temperature, and thus crop growth stage within a field can confound interpretation. To address problems of spatial variability, Bausch and Brodahl (2011) found that using soil electrical conductivity maps to spatially adjust the expected reflectance value for N-sufficient corn helped to address this problem.

Another source of error in sensor measurements is variation in measured values during a day. This problem was found by Oliveira and Scharf (2014) and was most pronounced with the Greenseeker reflectance sensor, which gave values that varied widely over the course of a day, substantially influencing the N rate recommended. This is consistent with the observations of Gwathmey et al. (2010). This is a weakness when using the Greenseeker sensor to guide N rate decisions, but should be correctible by updating the value for the high-N reference area every hour or so.

As mentioned in the section above, transmittance measurements, using hand-held instruments commonly referred to as chlorophyll meters, were first used for making yes/no decisions regarding application of additional N, either through fertigation (Blackmer and Schepers, 1995) or as an early season sidedress application (Piekielek and Fox, 1992). The latter application is of use mainly when manure N is part of the N supply, creating a significant proportion of fields where the correct decision is “no additional N needed”. Systems for making N rate decisions based on chlorophyll meter readings were later developed by Scharf et al. (2006a), Hawkins et al. (2007), and Varvel et al. (2007). The relationships between relative chlorophyll meter reading and optimal N rate (or suggested N rate) are similar for these three references, suggesting that these sets of available interpretations are robust. All three sources found stronger relationships between chlorophyll meter values and optimal N rate when meter values were expressed relative to values from a high-N reference area. As discussed in the section on reflectance sensors, this is an obstacle to adoption by producers. Relative to other plant-based measurements, chlorophyll meters provide an N rate decision much more quickly than do lab-based chemical analysis, but more slowly, with more labor and with a smaller sample size than reflectance sensors or aerial images. Chlorophyll meters can be GPS-enabled to allow the development of variable N rate prescriptions, but this process is slow and laborious.

Aerial images capture measurements that are, more or less, proportional to the reflectance of the crop canopy. In this way, they provide information that is similar to crop reflectance sensors, but with two advantages: (i) greater speed with which large areas can be assessed; this is of particular importance when rainfall may have caused substantial N loss; and (ii) the entire field is often sensed simultaneously or in a brief period, avoiding the issue with diurnal changes in proximal sensor measurements that is discussed above.

Aerial images also have disadvantages relative to proximal sensors: (i) weather can interfere, since a relatively clear day is needed; (ii) there is a delay for transit and processing between the time of image acquisition and the time the image can support N rate decisions in the field, and (iii) greater interference from soil background reflectance, which can be substantial early in the season (though new high-resolution aerial sensors show promise to remove this disadvantage). With proximal reflectance sensors, soil interference can be to some extent overcome by placing the sensors close enough to the canopy to enrich the proportion of plant material sensed. With aerial images, it can also be overcome, but less easily, by obtaining ultra-high-resolution images and then removing pixels representing soil before making N rate decisions (Scharf and Lory,

2002; Scharf et al., 2002). Advances in both aerial sensor capabilities and in computing power are increasing the practicality of this approach.

Unmanned aerial vehicles (UAVs) offer the potential to obtain high-resolution images that can support early season N rate guidance. For standard resolution images, UAVs are hard to scale relative to plane-mounted sensors, at least under current regulations, because a person in a plane can collect many times the imagery than a person with a UAV can collect.

Once the crop is fully canopied, information from standard-resolution aerial images can potentially predict optimal N rate (Sripada et al., 2005; Scharf and Hubbard, 2013) or yield penalty associated with N deficiency (Scharf and Hubbard, 2013).

The recent increase (June 2017) in satellite image frequency to near-daily by the Planet company (<https://www.planet.com/>) promises to remove one of the main limitations to the use of aerial imagery: the wait for image acquisition, which may be impeded by weather. Frequent satellite imagery brings the possibility to look back in time for a suitable recent image.

Strengths of Sensing Spectral Properties

The key strength of N rate predictions based on plant spectral properties is that they have usually been found to be more accurate than predictions based on soil samples, other soil properties, or crop yields. Greater accuracy translates to increased yield, reduced N cost, and reduced N loss to water and air.

Aerial imagery can assess crop N status over large areas quickly. This can be of foremost importance when N has been lost from fields due to wet weather. Identifying N stress and prioritizing fields for treatment can be accomplished much more quickly than by use of soil samples, plant samples, or proximal sensors. Rescue N applications of broadcast urea or UAN solution dribbled between rows with drop nozzles can then give large yield responses with minimal burn damage in N-stressed corn that is too tall to drive a tractor through (Nelson et al., 2011).

Proximal reflectance sensors and aerial photos have the great advantage of easily describing spatial variability in N status of fields (which is often large, see Fig. 1) compared with individually collected point samples such as hand-held meters, plant samples, or soil cores. Computer models may describe this variability easily, but are likely less accurate than plant sensors, due, at the least, to limitations in the accuracy of available soil data. Proximal sensors also provide immediate feedback about the N status of fields. Aerial images have the capability to estimate the N status of large fields and entire farms rapidly; entire farms can have the N status of their fields estimated in less than a day.

Limitations of Sensing Spectral Properties

Reflectance sensing is a recent technology, especially sensors with their own pulsed light source, and there remains substantial disagreement about how to translate reflectance values to N rates. Franzen et al. (2016) described the current status of interpretations for the central United States. More study comparing different interpretations is needed to determine which interpretations work best in which environments. This is even more true for aerial images. From a practical perspective, the need for high N reference areas also is a limitation that

increases the time and cost of using sensors, images, or other color-based approaches. This inconvenience can be overcome using the virtual reference concept, but available (limited) evidence suggests that accuracy may be compromised. Aerial images have limitations from weather delays in obtaining the images, and to a lesser extent the time to process the image. Chlorophyll meters deliver immediate results in the field, but the time to collect enough readings to accurately represent the N status of fields is often prohibitive.

Nitrogen Rate Recommendations Based on Chemical Analyses of Plant Tissue

The most widely known and oldest system for chemical analysis of corn tissue to evaluate N status is the ear leaf test for total N. This test is typically interpreted as sufficient or deficient, and an indication of deficiency in the ear leaf may be used to trigger a nominal N application. One of the first studies that established the potential for using ear-leaf N content to describe the N status of corn was completed by Bennett et al. (1953). They conducted eight experiments relating N fertilizer rate, yield, yield response, leaf N, and leaf N response. The leaf N concentration associated with 95% of maximum yield ranged from 2.6 to 3.1% in individual experiments, though it was not clear that maximum (non-N-limited) yield had been obtained in all experiments. In a later, much larger set of experiments, Dumenil (1961) concluded that there was a wide range of critical values for leaf N across 93 site-years.

In a more recent study, Cerrato and Blackmer (1991) attempted to calibrate ear leaf N to indicate quantitatively how much additional N was needed. Their approach to calibration was based on the foundational work of Macy (1936). They evaluated nutrient sufficiency as a function of crop response, however, it did not result in inflection points that could be used to determine critical concentrations. They found that within 55 kg ha⁻¹ of the optimal N rate, there was no relationship ($r^2 = 0.00$) between ear leaf N and difference from the optimal N rate. This suggests that the ear leaf N test would not be useful for distinguishing moderate N deficiencies, which is how the test is typically used. Within this range, samples below the “critical value” were just as likely to come from plots that received more N than needed as from plots that received less than the optimal N rate. Within 110 kg ha⁻¹ of the optimal N rate, there was a significant ($r^2 = 0.16$; $P < 0.01$) but weak predictive relationship between ear leaf N and difference from the optimal N rate, again suggesting minimal utility. When considering all data, including unfertilized plots in fields with high N need, predictive value increased considerably ($r^2 = 0.44$; $P < 0.01$) but this is of almost no practical value because farmers are not going to wait until sampling ear leaves to make their first N rate decision and N application. We are aware of no papers in the literature published after Cerrato and Blackmer (1991) that have shown how to use ear leaf N concentrations to distinguish moderate N deficiencies.

Several attempts have been made to develop N rate recommendations based on whole-plant total N early in the season. Some have met with modest success (Scharf, 2001), while others have not (Binford et al., 1992b; Evanylo and Alley, 1997). The latter two sampled the plants at 15 to 30 cm height, probably corresponding to V4 to V6 growth stages. Both studies

examined the relationship of aboveground corn N concentration to relative yield, but the relationships were too weak to use as a basis for N recommendations with Binford et al. (1992b) reporting an r^2 of 0.32 ($P < 0.05$), and Evanylo and Alley (1997) reporting an r^2 of 0.002 ($P = 0.78$).

Using EONR as the dependent variable rather than the more commonly used relative yield, Scharf (2001), found a considerably stronger relationship when plants were sampled for tissue N at V6 ($r^2 = 0.52$) than when they were sampled at V4–V5 ($r^2 = 0.22$). Even if this system could be developed to produce good-quality N rate decisions with V6 (30-cm) plant samples, the time to wait for lab analysis creates a logistical obstacle to fertilizing with a tractor-based applicator. This is a disadvantage compared with using reflectance or chlorophyll meter measurements at the same stage to make N rate decisions.

Tissue nitrate concentrations have been more widely used than any other tissue test for N over a broad range of crops (sugar beet [*Beta vulgaris* L.], cotton, potato [*Solanum tuberosum* L.], broccoli [*Brassica oleracea*], cauliflower [*B. oleracea*]), but sunlight effects on nitrate reductase and nitrate accumulation have proven to be an obstacle. This has held true for corn as well (Iversen et al., 1985), and may be one reason why Fox et al. (1989) found almost no relationship between stalk nitrate at the V5–V6 stage and ultimate N uptake of unfertilized plots over 87 site-years.

Corn Stalk Nitrate Test

The corn stalk nitrate test (CSNT) was developed to provide an assessment of the N status of corn at the end of the season (Binford et al., 1990, 1992c; Hooker and Morris, 1999; Fox et al., 2001; Forrester et al., 2012). This test was developed to take advantage of the fact that corn plants store nitrate in the lower stalk when excess N is available during the growing season. Excess nitrate remains in the lower corn stalk if the plant does not translocate the nitrate to the developing kernels during grain filling. Samples for the test are collected by cutting 20-cm segments of lower corn stalks at 15 and 35 cm aboveground level anytime between the one-fourth milk line stage of development to 3 wk past black layer development (Fox et al., 2001).

The CSNT is most useful for identifying excess applications of N. Identification of deficiencies is not as reliable because when nitrate concentrations are in the low range relative yields of corn vary from 25% of optimum to 100% of optimum (Binford et al., 1992c). One major limitation to the CSNT is that the test is a post-mortem estimation of N recommendations, which does not allow adjustments of N in-season. A plant tissue test earlier in the season would be of greater value, because results could be used to guide fertilizer applications that could improve yield. However, the stalk test fits well with the adaptive management approach that relies on either in-season evaluation or post-mortem evaluation of N status (see section below). Another limitation that has impeded the widespread adoption of the CSNT is the somewhat impractical sample collection in standing corn, handling of the samples, and laboratory sample processing protocols. These impediments will be greatly reduced if users employ the more practical, faster, and simplified methods suggested in Ketterings et al. (2017b).

Strengths of Plant Tissue Testing

The primary advantage of plant tissue testing is widespread acceptance. A small amount of data shows better predictions from early season whole-plant N analysis than from soil samples. A substantial body of data suggests that the late-season stalk nitrate test provides accurate feedback regarding N rate, and is the only tool for identifying instances of over-application of N.

Limitations of Plant Tissue Testing

Ear leaf N is the most widely used test in corn, but research showing that N rate can be accurately predicted from ear leaf N analysis is lacking. An additional problem with the ear leaf N test is that at the time when the ear leaf is sampled the availability of application equipment to apply the N is limited. Managing spatial variability in N status is difficult with plant tissue testing because sample collection is labor intensive. Needing to wait for transport of the samples to a lab and lab analysis before a decision can be made is another limitation.

Computer Simulation Models and Weather Databases

Location- and time-specific N recommendations can be made through the application of dynamic simulation models of the weather–soil–crop system, which can provide information for farmers to adjust in-season N applications to more precisely match crop N demand (Kersebaum, 1995). Because weather interacts with soil properties to critically affect prediction of N dynamics, the inputs should be integral components of model-based recommendation systems (Tremblay et al., 2012).

For corn N recommendations in North America, two computer simulation model-database systems have been developed by universities: Adapt-N (Melkonian et al. (2008), now commercialized) and Maize-N (Setiyono et al., 2011). Private companies also have developed computer simulation model-database systems to aid decisions about N rates for corn: Monsanto's FieldView Pro and DuPont Pioneer's Encirca. The algorithms used in these programs are proprietary, and there are no published studies evaluating the effectiveness of the programs.

Maize-N and Adapt-N both include dynamic simulation models that aim to incorporate system complexity through the representation of relevant soil and crop processes. The models allow for more field-specific recommendations and incorporate real-time weather and long-term climate information as well as local soil and crop management factors. Both are the result of long-term research efforts involving model development, parameter calibration, and field validation, and are documented in peer-reviewed publications. Both also offer estimates of uncertainty around the recommended rate and provide tabular and graphical outputs that provide additional diagnostic information on simulated N dynamics.

Adapt-N

The Adapt-N tool, developed at Cornell University, is server-based and accessible through any internet-connected device that supports a web browser. Adapt-N is now available from the Agronomic Technology Corporation at: <http://www.adapt-n.com/>. It is built around the Precision Nitrogen Management (PNM) model (Melkonian et al., 2005, 2007), which in turn is an integrated and enhanced combination of

the LEACHN model (Hutson, 2003), and a corn N uptake, growth, and yield model (Sinclair and Muchow, 1995). An important feature of Adapt-N is its dynamic access to gridded high-resolution (4 by 4 km) weather data (Tmax, Tmin, Precip; Table 3), which allows for field-specific and timely adjustments to the model output. Adapt-N is therefore primarily conceived for in-season N management (sidedress or high-clearance applications) when weather-based N recommendations are most valuable. The high-resolution weather database is derived from routines using National Oceanic and Atmospheric Administration's (NOAA) Rapid Update Cycle weather model (temperature) and operational Doppler radars (precipitation). Both temperature and precipitation from observed weather station data are used to correct NOAA estimates and generate spatially interpreted grids (Belcher and DeGaetano, 2005; Wilks, 2008).

Soils information used in Adapt-N is derived from NRCS SSURGO datasets (<http://soildatamart.nrcs.usda.gov/>). The Adapt-N tool combines various user inputs (Table 3) with soil and weather data to dynamically simulate early season crop and N dynamics and to estimate soil N supply and crop uptake. These estimates are then incorporated into a mass balance equation with stochastically modeled estimates (using long-term climate data) of remainder-of-season N mineralization and losses, rotation N credits, and crop-fertilizer and uncertainty cost factors (Moebius-Clune et al., 2012).

Adapt-N's underlying soil model, LEACHN, has been extensively tested (Jabro et al., 1994; Jemison et al., 1994; Sogbedji et al., 2001a, 2006). The crop subroutines were developed as reported in Muchow and Sinclair (1991), Muchow et al. (1990), Sinclair and Amir (1992), and equations and validation are presented in Sinclair and Muchow (1995). The combined PNM model was tested by Sogbedji et al. (2006) and Melkonian et al. (2010) and showed low prediction errors. Graham et al. (2010) applied the model to generate within-field site-specific N recommendations.

A dynamic mass-balance equation is used to generate a N recommendation in Adapt-N (Moebius-Clune et al., 2012):

$$N_{\text{rec}} = N_{\text{exp_yld}} - N_{\text{crop_current}} - N_{\text{soil_current}} - N_{\text{fut_gain-loss}} - N_{\text{rotation}} - N_{\text{profit_risk}} \quad [12]$$

These terms have analogies to those in Stanford's equation and its derivatives, but in this case focus on a recommendation for a specific production environment (field, management) at a specific time (day of growing season). The $N_{\text{exp_yld}}$ is the (expected) total uptake of corn at physiological maturity, or N_Y in Eq. [1]. The $N_{\text{crop_current}}$ is the total uptake of N up to the stage of corn development at the date the simulation is run. This represents a new term $N_{Y(t)}$ that adds an evaluation of the portion of total N already taken up at time t in the season. The difference, $N_{\text{exp_yld}} - N_{\text{crop_current}}$ is the N uptake requirement for the remainder of the season. The $N_{\text{soil_current}}$ is the amount of plant-available N in the soil, also at time t . It therefore is a temporal assessment of N_S in Eq. [1] and can be included as a new term $N_{S(t)}$. Similarly, $N_{\text{fut_gain-loss}}$ is the plant-available N in the soil after time t through the end of the season (estimated from 30-yr climate data) and can be added as another term $N_{S(t+)}$. For Adapt-N, $N_{S(t)}$ and $N_{S(t+)}$

Table 3. Summary of features and inputs for Adapt-N and Maize-N tools.

Feature/Input	Adapt-N	Maize-N	Comments
Time scale	Real-time, daily high-resolution weather data. Uses historical climate data for post-date estimates	Long-term using historical daily climate data inputs for yield estimation and N mineralization with the option of in-season weather data for N mineralization	Key difference between the tools
Optimum N estimation	Mass balance: deterministic (pre)-stochastic (post) with crop-fertilizer price ratio	Response curve–N credits–efficiency, with crop-fertilizer price ratio	Adapt-N incorporates pre-set seasonal crop-fertilizer price ratios; Maize-N employs user inputs
Climate-weather inputs	Near-real time: Solar radiation; Evapotranspiration (ET); max-min temperature; precipitation	Solar radiation, max-min temperature; precipitation; ET	Solar radiation and ET are (or can be) estimated in both tools.
Soil inputs	Soil type or series name related to NRCS database; rooting depth; slope; soil organic carbon (SOC)	SOC; texture; bulk density; acidity; measured soil nitrate before planting (opt.)	Default values available for some inputs
Crop inputs	Cultivar (grain, silage, sweet); maturity class; population; expected yield	Maturity rating; date of planting; population; grain price	Adapt-N uses user-defined yield; Maize-N estimates yield, with possible user modification
Management inputs	Tillage (type, time, residue level); irrigation (amount, date); manure applications (type, N & solid contents, rate, timing, incorporation method); previous crop characteristics	Tillage (type, time); irrigation; manuring (type, N and moisture contents, rate, timing); previous crop and yield	
N Fertilizer inputs	Multiple: Type, rate, time of application, placement depth	Basal and in-season: Type, price, rate, time of application, N from irrigation	
Graphical outputs	N contributions and uptake; N losses (total, NO ₃ leaching and N ₂ O); N content dynamics; crop development; weather inputs	Soil C–N dynamics; yield response curve; N contributions and uptake; yield indicators; efficiency indicators; weather inputs	
Other	Web accessible; option for automatic daily updates by email or text message; batch data upload capability. Available for 18 U.S. states in the Northeast and Midwest.	Purchased and downloaded to PC. Input/output features. Tested for conditions in the western Corn Belt	Both tools have diagnostic and reporting features, and facilitate evaluation of management alternatives

also include contributions from labile N sources (manure and rotational/cover crops) that are integrated in simulations and therefore also include Q_{LN} , Q_{RLN} , Q_{MON} , Q_{RMON} in Eq. [10]. The $N_{\text{fut_gain-loss}}$ term also includes an estimate of the applied N that can be expected to be lost post-application from the soil–plant system and can be denoted $N_{F(\text{loss})}$. It adjusts the recommended N upward to account for these losses and therefore is analogous in function to the E_F term in Eq. [1]. The N_{rotation} term represents plant-available N from a previous legume crop and is also a contribution to Q_{LN} . The final term, $N_{\text{profit_risk}}$ adjusts the recommended N rate downward when N prices are higher relative to crop prices, and also accounts for the asymmetric economic risks associated with insufficient vs. excessive fertilizer rates. This factor allows the N rate based on crop uptake requirements to be adjusted to meet economic objectives and will be denoted $N_{F(\text{econ})}$. Rewriting Eq. [12] using nomenclature related to Stanford's equation yields:

$$N_F = N_Y - N_{Y(t)} - Q_{S(t)} - Q_{S(t+)} - Q_{LN} + N_{F(\text{loss})} - N_{F(\text{econ})} \quad [13]$$

This equation demonstrates that in Adapt-N, both N_Y and N_S in Eq. [1] are itemized into two temporal categories with

the dividing point being the time within the season when the model is run. Also, the Q_{LN} term is itemized separately from the $Q_{S(t)}$ and $Q_{S(t+)}$ terms. Individual efficiency (E) factors are omitted for $Q_{S(t)}$, $Q_{S(t+)}$, and Q_{LN} . The fertilizer recovery efficiency (E_F) is also omitted, but the $N_{F(\text{loss})}$ term is used instead to adjust the N rate upward to account for the cumulative effect of the various inefficiencies in plant uptake of the various plant-available N sources, including the fertilizer application itself.

Maize-N

The Maize-N tool (<http://hybridmaize.unl.edu/maizen.shtml>), developed at the University of Nebraska-Lincoln, is an adaptation of a dynamic-K model for simulating C and N mineralization from SOM and crop residuals (Yang and Janssen, 2000, 2002), and the Hybrid-Maize model (Yang et al., 2004) for estimating corn yield. The Hybrid-Maize model was developed to simulate corn growth and yield under rainfed and irrigated conditions. Estimates for site crop growth and yield parameters are averages of long-term yearly simulations using historical weather data, soil information, and crop management practices (planting date and density, hybrid maturity, etc.; Table 3). The Maize-N tool also considers N mineralization from SOM, root stubble, as well as aboveground residuals whose incorporation into soil is controlled by tillage

management. Maize-N accounts for differences, by means of efficiency parameters, in recovery efficiency of N fertilizer, carryover N from the previous cropping season, and N released through mineralization processes. It also considers N leaching beyond maximum crop rooting depth. Maize-N is currently offered as a software package that is installed on personal computers.

Maize-N mechanistically estimates indigenous N supply and relates it to yield through an N uptake requirement to yield response function based on a database from research and farmer field trials. It combines crop response with physiological and N use efficiency factors as affected by soil and fertilizer management to formulate a recommendation (Setiyono et al., 2011). Testing of the Hybrid-Maize tool is reported in Yang et al. (2004), Raymond et al. (2009), and Grassini et al. (2009), which showed good agreement with field-measured crop variables in validations using known yield and weather conditions. The Maize-N tool demonstrated good agreement between estimated and measured EONRs based on trials in western Corn Belt states under both dryland and irrigated conditions (Setiyono et al., 2011, Thompson et al., 2015).

Maize-N formulates N recommendations by combining components of Eq. [10] with both empirical and mechanistic models. The N recommendation is based on the derivative of a spherical-plateau function that describes the relationship of N uptake requirement to corn yield (Setiyono et al., 2011). This derivative calculates the EONR.

Maize-N uses modules from Hybrid Maize (Yang et al., 2004) to estimate potential yield (Y_p), which is the yield possible with no nutrient limitations within a given environment and set of management practices. Potential yield is greater than what can be attained in practice. Attainable yield (Y_a) is determined one of two ways: (i) as a user-input, based on yield history, or (ii) as a fraction of Y_p , where $Y_a = 0.85Y_p$. The fraction 0.85 was considered the average proportion of Y_p that is realistic to target.

Unfertilized corn yield (Y_0) is estimated from predictions of the quantity of N mineralized from SOM (Q_{SON} in Eq. [10]), using a mechanistic soil C mineralization model (Yang and Janssen, 2000). The recovery efficiency (E_{SON}) is a constant equal to 0.85, so $N_{SON} = 0.85Q_{SON}$. An empirically derived spherical function, based on the theory of the QUEFTS model (Janssen et al., 1990) relates Y_0 to N_{SON} .

The amount of fertilizer to apply is based on the expected yield response ($\Delta Y = Y_a - Y_0$). An empirically derived linear function relates agronomic efficiency (AE_N) to ΔY . Agronomic efficiency is the increase in yield per unit of applied N (kg grain increase (kg N)⁻¹). The recommended N rate is then calculated as: $N_F = \Delta Y / AE_N$.

Model Comparison

Adapt-N and Maize-N use comparable inputs and outputs and generally have the following main features in common: (i) dynamic simulation of soil and crop processes (water, N, crop development, etc.) based on information on soil, crop, and management, and daily weather; (ii) scale-independence and potential use at field and subfield level; (iii) provision of uncertainty estimates for N rates; (iv) incorporation of economic considerations (crop–fertilizer price ratio; uncertainty); and

(v) extensive additional diagnostic information on simulation results. In addition, both tools allow for alternative management scenario analyses.

The tools vary substantively in several ways (Table 3):

- Adapt-N dynamically accesses high-resolution weather data, which allows for real-time optimization and automated daily updates for a particular location. Maize-N estimates attainable yield using historical climate station data or user-provided weather information, focusing on long-term (average) optimization for a particular location. Maize-N has the option of using current season weather data for estimation of N mineralization from SOM.
- Adapt-N uses a deterministic-stochastic mass balance equation to compute optimum N rates, while the Maize-N recommendation is based on a combination of mechanistic and empirically derived equations. Also, Maize-N uses model-estimated corn yields (with possible user modification), while Adapt-N employs user-defined yields.
- Adapt-N simulates a broader set of N dynamics, notably N losses (leaching and denitrification), which allows incorporation of seasonal rainfall effects on N losses (Tremblay et al., 2012), and provide estimates of leaching and denitrification losses, including N₂O, which are of interest to not only farmers, but also to regulators, environmental organizations, and the non-farming public. Maize-N also includes N leaching loss but not denitrification and other gaseous losses.
- Maize-N is installed on PCs, while Adapt-N operates in a web-based environment and is internet accessible.

In general, Adapt-N facilitates real-time management of N in regions where seasonal weather variability is a critical factor in N fertilization. Maize-N has strengths in yield estimation, and is expected to perform well in dryer rainfed and irrigated environments where seasonal weather and N loss variability are minimal, or when in-season adaptation is not pursued (Setiyono et al., 2011).

Validation in On-Farm Trials

The utility of model-based N recommendation systems is defined by their ability to accurately estimate corn N needs for an individual field or parts of a field and a particular season. Validation of the Maize-N tool based on nine field experiments in Nebraska and South Dakota in 1999, 2000, 2007, and 2008 (Setiyono et al., 2011) showed that the tool estimated EONR with greater accuracy than conventional empirical N recommendation approaches that use yield goals and N supply generalized over large regions. Maize-N root mean square error (RMSE) values were 21 kg ha⁻¹, while conventional recommendations showed RMSE values of 33 to 61 kg ha⁻¹. A more recent field study conducted at 12 sites in North Dakota, Nebraska, and Missouri found that N rate recommendations from Maize-N protect crop yield better than sensor-based methods (Thompson et al., 2015). These RMSE values for Maize-N are not directly comparable to the RMSE values below for Adapt-N because the Maize-N validation was completed post hoc with known yield values and weather conditions while Adapt-N was validated a priori with the decision about each N sidedress rate made without measured yield values and unknown weather conditions after sidedressing.

Adapt-N was evaluated through 113 replicated on-farm strip trials in New York and Iowa during 2011 to 2014 where recommendations from Adapt-N were compared with conventional grower practice under a variety of rotations and management practices (Sela et al., 2016). Marginal profits were on the average \$65 ha⁻¹ higher and N inputs 45 kg ha⁻¹ lower when Adapt-N estimated N rates. Simulated estimates of post-side-dress N losses for the four growing seasons averaged 36% lower for leaching and 39% lower for gaseous losses in this relative comparison of the growers' rate of N and the Adapt-N rate of N (Sela et al., 2016).

Adapt-N was also evaluated in 16 on-farm multi-rate replicated trials in New York, and 23 in Indiana, Ohio, and Wisconsin (Sela et al., 2017). By basing recommendations on local conditions, Adapt-N achieved RMSE values of 33 kg ha⁻¹ and bias of -12 kg ha⁻¹ (compared with 85 and 64 kg ha⁻¹, respectively for the Cornell N Calculator) in the New York trials, and 33 kg ha⁻¹ and bias of -10 kg ha⁻¹ (compared with 49 and 39 kg ha⁻¹, respectively for the MRTN) in the Midwestern trials. Adapt-N achieved a mean loss in profit below the post hoc calculated EONR of \$19 ha⁻¹ in New York compared with \$83 ha⁻¹ for the Cornell N Calculator, and reduced leaching losses by 53% and gaseous losses by 54% (Sela et al., 2017). Research to evaluate Adapt-N and other computer simulation model-database systems is ongoing in the Corn Belt and in the Southeast United States, which will provide additional information about the effectiveness of this approach to improve N recommendations.

Strengths of Computer Models

Process-based models allow for the dynamic simulation of the factors that affect EONRs of individual fields to obtain more dynamic and locally adaptive N rate recommendations. Models therefore address a weakness of the static, generalized recommendation systems that can provide a reasonable average recommendation in most years but are overall imprecise for individual fields. Also, model-database tools intrinsically adapt to climate change, and readily accommodate technology development (e.g., incorporation of future hybrid characteristics) and successive refinement (e.g., updates based on results from field trials).

An analysis of the strengths and weaknesses of model-database approaches to estimating N fertilizer rates is complicated by the diverse set of alternative approaches to which they could be compared. The primary concern for a new recommendation system is whether it increases profits for the farmer, as this will drive adoption. A secondary concern is whether the new tool results in reduced environmental effects, which prompts societal interest. Preliminary results for Maize-N and Adapt-N are encouraging on both counts. Results also suggest that models and databases can reduce uncertainty and risk, that is, farmers can adapt to field-specific conditions and reduce the need for insurance applications.

Both Maize-N and Adapt-N have strong diagnostic features and allow for scenario testing. User insights into soil-crop system dynamics can be informative in supporting broader sets of management decisions. Both tools provide information on soil N status and crop development that can be verified through field measurements (e.g., late spring and end-of season soil nitrate tests; crop vegetative stage). Adapt-N also monitors soil water status and provides irrigation advice. Overall, by providing results on the process simulations, the model-database

tools allow for a more sophisticated user approach compared with the generalized recommendation methods, and could also potentially be used in combination with other tools like soil or crop sensors (Scharf et al., 2011). Finally, the integration of the dynamic model tools into existing GIS platforms facilitates data integration and adoption.

Limitations of Computer Models

A disadvantage of model-database tools is that the data-driven approach requires inputs that pose a cost to the user or database information that may contain inaccuracies (e.g., SSURGO; Gelder et al., 2011). Nevertheless, most requisite information relates to standard management information or application records (SOM content, hybrids, manure and fertilizer applications, etc.). This is intrinsic to precision (data-driven) agriculture in general, as greater accuracy can be achieved only with information about resources and management, which is often facilitated through links with farm management software systems. Both tools use yield targets that are increasingly available from yield monitors. Yield estimates can still be challenging to farmers (Rehm and Schmitt, 1989), although they nevertheless often make precise predictions (within 5% of achieved yields; Sela et al., 2017). Changes in estimated yields, however, can substantially effect N fertilizer predictions from the model (Sela et al., 2017).

Also, since weather effects on N dynamics are most significant in the early growing season (Sogbedji et al., 2001b), model-database N management tools are most effective when used with in-season N management, which requires sidedressing equipment or custom application of N with high-clearance equipment.

One of the limitations of the Maize-N model is that it relies heavily on the setting of N recovery efficiency for each of the N sources, including SOM mineralization, residue N from the last crop, crop residues and manures, and N from irrigation water. Although the default settings are based on research data, they may not always represent farmers' practices and soil and field conditions at each field. Calibration of those parameters is possible but requires careful design of field trials and techniques of ¹⁵N labeling for differentiating N from different sources.

Although the cost of development has been mostly borne by public funds, the tools pose ongoing expense in infrastructure maintenance, monitoring, and updating. A commercial version of these tools requires appropriate user fees, although the high scalability of computer technology can reduce costs with widespread adoption. Costs will generally be higher than the approaches that involve generalized recommendations (MRTN; Yield-based systems), but lower than variable-cost methods that involve soil or tissue testing (sampling and analysis costs) and sensor-based approaches (equipment purchase and field operation costs).

ADAPTIVE MANAGEMENT: A PROCESS TO IMPROVE NITROGEN RECOMMENDATIONS FOR CORN

Nitrogen recommendations for the foreseeable future in humid regions will poorly predict the amount of N needed for corn at individual fields. The evidence for this is discussed above and reported in Blackmer et al. (1992) and Lory and Scharf (2003) for the yield goal method, and is shown for the MRTN method in Fig. 10. Current recommendation systems

should be considered starting points for deciding what rate of N to apply to individual fields (Ketterings et al., 2017a). Improving generalized N recommendations for individual fields will require modifying the recommendations in some organized process.

Adaptive management is an already established process that is tailor made for improving generalized N recommendations for individual fields. Adaptive management has not typically been used at the field level in agriculture. A definition of adaptive management for agriculture developed by the multi-state coordinating committee NEERA 1002 entitled “Adaptive Management for Improved Nutrient Management” defined adaptive nutrient management for agriculture as: “A process of developing improved management practices for efficient production and resource conservation by use of participatory learning through continuous systematic assessment. Participants include producers, agricultural service providers, policymakers, regulators, scientists, and other interested stakeholders.” This definition was developed in response to the uncertainty in the amount of N needed by corn, and the desire to have a formal process to fine-tune N recommendations.

The reason adaptive management has not been used at the field level in agriculture may be related to how it was first defined by ecologists. Adaptive management as a process to better manage large ecosystems was first developed in the 1970s and 1980s by Holling (1978) and Walters (1986) from the University of British Columbia. The process was originally created in response to the inefficiency of static plans for Environmental Impact Assessments, which became common after passage of the National Environmental Policy Act of 1969 (Holling, 1978). Conservation biologists needed a process to develop plans, usually by government or quasi-government agencies, for management of ecosystems that were dynamic and not static. The iterative process is shown in Fig. 13A.

In agriculture, by contrast, the adaptive N management process to better manage N is completed on a field or a within-field basis, usually less than 36 ha in size, rather than across a large ecosystem, which typically cover thousands or millions of hectares. Evaluations of new N practices on a field scale enables relatively easy, direct, and timely collection of data about the performance of the practices, while difficulties of evaluating new practices across large land areas like ecosystems often has been a reason for failure of traditional adaptive management programs (Gregory et al., 2006). Another advantage is in agricultural adaptive management farmers are the implementers

of improvements in practices on the landscape and not agency personnel (Iowa Soybean Association, 2014; Ketterings et al., 2013; Ketterings, 2014). The improvements also directly relate to the economic, environmental, and social goals of the farmers, rather than to improvements in the ecosystem that often have only an indirect relationship to the citizens living in the ecosystem. The direct management of the land by farmers and the relative ease of data collection makes the adaptive management process in agriculture a technique of tremendous potential to improve farmer practices.

The key factors in adaptive N management are the establishment of a process to objectively evaluate N practices at the field or subfield level, compilation of the results of the evaluations in an easy to understand format, and discussion of the results by a knowledgeable agronomist either one-on-one with farmers or in group meetings with farmers to understand how the results can be used to improve N management (Chapman et al., 2016).

The five steps of adaptive N management (Fig. 13B) are familiar to agricultural service providers who strive to help farmers improve practices by using demonstration plots. However, there are two important differences between N demonstration plots and evaluations of N practices in an adaptive management program. The first is that adaptive N management requires scientific rigor, which is not always the case for demonstrations; many demonstrations are not replicated. The second is that adaptive N management includes time for learning through discussion by farmers in winter meetings about individual and aggregate results of scientifically rigorous evaluations of practices, while results of demonstration plots are typically discussed informally at field days or the results are used as lecture material in winter meetings (Chapman et al., 2016; Iowa Soybean Association, 2014), which is not as effective at increasing learning (Bell and McAllister, 2013).

A typical adaptive management method to obtain robust evaluations of N management at the field level to fine-tune N practices is to perform replicated strip trials comparing either two or more rates of N or different forms, timing or placement of N. Two treatment replicated strip trials, usually the farmer N rate or an N rate from a recommendation system like the yield goal system or the MRTN system, and a rate that is 45 kg N ha⁻¹ greater or less than the farmer or recommendation system rate, enable farmers to refine N recommendations (Kyveryga et al., 2013). Refinement of N recommendations on an individual field basis is clearly needed for all

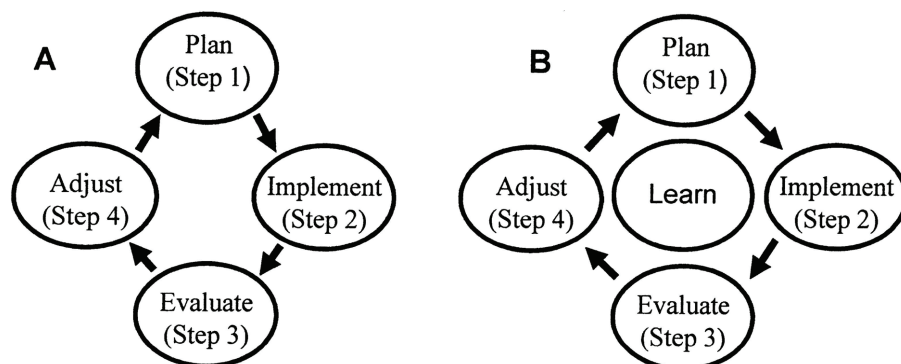


Fig. 13. (A) Four steps in a traditional adaptive management program; (B) Adaptive management in agriculture adds an explicit step of learning, that occurs at all steps, but mainly after the evaluate step.

recommendation systems based on the information provided throughout this paper. All N recommendations should be considered starting points for estimating the amount of N needed at individual fields and not accurate predictions of the exact amount of N fertilizer needed by corn. Results of two treatment trials over a few years enables farmers to obtain objective evidence about the N response on their fields. This is the first step toward an adaptive approach to N management.

Another method to adaptively manage N is to use a tool that provides an objective measurement of the N status of corn fields such as the CSNT. What is viewed as a disadvantage of the CSNT by many farmers and farm advisors, not being able to act on the results until next season, makes CSNT results ideal for adaptive management. The CSNT results give an estimate of the N status of the field during the growing season, and the information can be assessed in the context of the environmental conditions during the growing season before deciding on an N rate for the upcoming season. When the CSNT is paired with aerial images of corn fields collected shortly after tasseling the results accurately estimate the N status of corn fields at the end of the season (Kyveryga et al., 2010). The results of CSNTs collected over 2 or more years from the same field when combined with field history and rainfall information is an excellent technique to refine N recommendations. Another more recent use of the CSNT combines CSNT results from surveys of the N status of large land areas such as the state of Iowa with field information about previous crop, N rate, form, and timing along with early season rainfall data to enable much more informed decisions about the risk of typical N management practices (Anderson and Kyveryga, 2016). These types of results from farmers' fields when discussed in winter meetings with farmers can greatly improve the efficiency of N practices with reduced risk to farmers.

Including time for discussing results of evaluations in group settings is an effective way for farmers to learn from the results (Padgett and Lasley, 2004). Providing results to individual farmers in one-on-one meetings, however, also is effective. Structuring an adaptive N management program to ensure ample time for learning from the results whether in one-on-one sessions or groups meetings can significantly increase the adoption of improved practices. One simple but effective method for farmers to learn more effective N management is by benchmarking, which is defined as "the search of those best practices that will lead to the superior performance" (Camp, 1989). In adaptive management meetings benchmarking is accomplished by showing both the aggregate yield and distribution of yield across all strip trials for various management and field conditions. Farmers can compare their results to the results of the group. Benchmarking is a type of best practice for adult learning, and building a meeting around a set of best practices for adult learning (Bell and McAllister, 2013) will make effective use of the time, effort, and money expended to obtain the results.

Adaptive N management is possible largely because many farmers have yield monitors on their combines. Yield monitors provide farmers with an easy way to obtain accurate yield measurement from their fields in digital format. Measuring yields of replicated strip trials that span the length of a field only minimally slows harvest and makes it easy for farmers to complete scientifically valid experiments. Accurate yields can

be obtained from crops that cannot be harvested by a combine with a yield monitor, such as silage corn, but the time and expense needed to obtain accurate yields limit the number of trials.

Adaptive management programs usually involve creating networks of farmers who cooperate to establish common evaluations of practices (Chapman et al., 2016). Networks of farmers have been shown to increase learning by farmers (Kilpatrick et al., 2003) and are an effective method for evaluating practices and for extending the results beyond the network (Gianatti and Carmody, 2007). An example of how a practice can be evaluated by a network of farmers is when 20 farmers decide to complete replicated strip trials comparing their normal rate of N to a rate 50 kg ha⁻¹ less or greater than normal, and run the trials for 3 yr. The network would include scientists and agronomists who help the farmers decide how to establish scientifically valid evaluations that provide answers to questions raised by the farmers. The protocols for such trials have been published (Kyveryga et al., 2016) and can be used in discussions with farmers. The scientists would summarize the results of the evaluations and organize the meetings to maximize learning from the results.

A large advantage of adaptive management programs that create networks of farmers is the results from hundreds of trials across many years can be combined by the scientist to improve N recommendations and inform agricultural policy and regulations. The Iowa Soybean Association's On-Farm Network (<http://www.isafarmnet.com/>) and the Indiana State Department of Agriculture's INfield Advantage program (<http://www.infieldadvantage.org/>) are probably the best examples of network of farmers that create sufficient data to improve N recommendations and to inform agricultural policy and regulations. Data from the On-Farm Network has been published in numerous venues. One example is a scientific publication about the probability of yield response to N fertilization at 56 fields across 2 yr (Kyveryga et al., 2013). Factors affecting the yield response were June rainfall, timing of N applications, amount of SOM and previous crop. The probability these factors had on reducing yield response was calculated. For example, when June rainfall was below normal sidedress applications were 20% riskier than spring applications. The number of locations and years of trials reported in this study are not sufficient for compelling conclusions about factors affecting yield response to N fertilization, but these results are from only one network of farmers. Creating a national network of farmers dedicated to generating evaluations of N response in a systematic way with collection of appropriate metadata about each trial could greatly improve knowledge about the factors affecting yield response, which could be used to improve N recommendations. The same data could be used to inform agricultural policies and regulations.

Strengths of Adaptive Nitrogen Management Programs

Adaptive N management programs allow farmers to fine-tune generalized N recommendations, which increase N use efficiency, profitability of corn production and should help farmers reduce N loss to the environment. Adaptive N management programs when used to create farmer networks involve large numbers of farmers and allow creation of large databases of N response trials. Such databases with their accompanying metadata can be used to rapidly and accurately improve N

recommendations and inform agricultural policies and regulations. With most farmers in the Corn Belt of the United States operating combines with yield monitors, adaptive management as practiced by networks of farmers is currently the most reliable method to estimate N needs of individual fields.

Limitations of Adaptive Nitrogen Management Programs

Establishment of adaptive management programs requires scientists, agricultural service providers, and farmers to work together in an unfamiliar way. Scientists are facilitators in adaptive N management programs rather than leaders, which is a non-traditional role for them. Ecologists who facilitate traditional adaptive management programs sometimes describe their involvement in the programs as “leading from behind” (Nelson, 1994). Skills at facilitation of learning at meeting rather than providing lectures will need to be developed by scientists in adaptive N management programs. Scientists will also need to develop new statistical skills for analysis of large amounts of messy data. Datasets from adaptive N management programs usually are best analyzed by using statistical techniques such as logistic regression, hierarchical models, and Bayesian methods, which are not typically used by agronomic scientists.

Agricultural service providers will need to develop similar facilitation skills as scientists. They will need to learn to facilitate meetings rather than lead meetings. Agricultural service providers traditionally provide direct answers to questions from farmers. In discussions with farmers about results of evaluations completed on the farmers’ fields much more learning occurs if the farmers have time to explore the data rather than having an answer presented to them by an expert (Bell and McAllister, 2013).

Farmers involved in adaptive N management programs in farmer networks will need to agree to allow scientists to combine the data from their farm with data from other farms to make the most effective use of the results. Farmers often are uncomfortable allowing information about N management on their fields to be included in a large database of N response trials. Creation of reporting guidelines and data handling protocols agreed to by scientists, farmers, and agricultural service providers may alleviate the concerns many farmers have about providing data from their farm to a large database for analysis by scientists for the benefit of all farmers.

A FRAMEWORK FOR IMPROVING NITROGEN RECOMMENDATIONS FOR CORN

Finding methods to improve N recommendations for corn is essential to provide producers with optimum yield and profit, while minimizing environmental losses and detrimental effects of N. It will be years before major advances in the accuracy of N recommendations occurs, but while working toward improved recommendations, the promotion of current N best practices supported by current extension recommendations in each state, the USDA Natural Resources Conservation Service through the 590 Standard (USDA-NRCS, 2011), and industry groups such as The Fertilizer Institute and the International Plant Nutrition Institute should continue. In many cases, N use efficiency could be significantly improved, and environmental effects of N use lessened, if current recommended best management practices are used by farmers.

Studies have indicated that farmers often do not use the nutrient management tools available to them (Shepard, 2005; Osmond et al., 2012) or that regional practices may encourage application of N many weeks or months before crop uptake, which although useful managerially, may increase N losses (Randall and Vetsch, 2005; Bakhsh et al., 2006). Encouraging the most efficient timing, source, and placement of N fertilizer, three of the 4Rs of nutrient management (IPNI, 2017), is essential as we move forward in developing better rate recommendations.

Recommendation procedures that focus only on the relationship between fertilizer N rate and yield, are not likely to be successful because timing, source, and placement interact with N rate. Most of the uncertainty of predicting optimal fertilizer N rates is related to weather, particularly water availability—either excess or deficit—and its influence on soil N supply and loss of fertilizer N. In regions where rainfall is less, such as semiarid, irrigated regions of the western Corn Belt, the potential for using a mass balance approach to fertilizer N management is greater. For irrigated corn systems, accounting for inorganic soil residual N, mineralized soil N, and attainable yield—combined with efficient timing and placement—has been shown to provide good estimates of EONRs at the start of the growing season (Dobermann et al., 2011; Wortmann et al., 2011). However, use of such approaches has met with less success in higher rainfall regions of the Corn Belt. Promising techniques, such as sensor technologies and modeling using both long-term and real-time weather data, may better match real-time N fertilizer rates to needs (Raun et al., 2011), but these technologies have only recently emerged and not all farmers have access to them. Further, real-time N application on corn may involve equipment or management time that is unavailable.

With the expanded Stanford equation (Eq. [10]), it is possible to propose ways to measure or better estimate many of the individual parameters in this equation. Figure 3 suggests possible measurements or approaches for improving the estimates in the N recommendation equation. It is clear from Fig. 3 that there are some critical areas that should be addressed directly. These include better integration of measurements such as the pre-plant nitrate test, the pre-sidedress nitrate test, SOM, plant tissue tests and plant sensors, and manure analysis into the recommendation equation. The effect of weather on many of these factors is obvious. This challenges scientists to find ways to better account for real-time or historical weather effects through models or by grouping parameters based on localized weather conditions.

One way to start improving N recommendations could be to use the concepts and factors from the Stanford Equation but substitute more readily available information. For example, rather than starting with the internal N requirement of the crop we could start with a base recommendation from the grouped economic optimum approach or MRTN approach. Then the fertilizer equivalence of variable sources of N such as manure and legumes could be used to adjust the base recommendation. For this to work optimally, the conditions for the base recommendation would need to be defined as explicitly as possible, for example, soil types, climatic zone, tillage management, crop rotation, SOM range, soil nitrate range, manure, legumes, etc. This could start with empirically derived factors to adjust the base recommendation and then through adaptive management, these factors could be refined for localized conditions. As new research is conducted, better ways to practically

estimate the factors in the Stanford equation could be substituted for the assumed factors. This has the advantage of the familiar, whether we relate the factors to the Stanford equation or not, because it is a common approach to making and adjusting N recommendations. Linking this to the expanded Stanford equation, however, provides a structure to guide adaptive nutrient management to improve N recommendations.

Alternatively, we could use the expanded Stanford equation (Eq. [10]) with assumed amounts of available N and assumed coefficients, or empirically estimated quantities such as soil N supplying capability or manure N supply. The advantage of this approach is that it retains the structure of current yield-goal N recommendation systems and makes clear how the various factors contribute to meeting the crop N requirement. Models could play a key role in integrating information into the Stanford equation to make more accurate N recommendations. Models fit with the adaptive management approach because localized empirical data could be used to improve the accuracy of the estimates by the models, for example, legume N contributions in local cropping systems. One disadvantage of models may be that the current process for making N recommendations is a quick process that involves little to no data input by farmers or agricultural service providers, while models require input of substantial field-specific data. Much of the data, however, only needs to be entered once for a field. Another potential disadvantage of models is that they may provide a false sense of mechanistic accuracy, including those for sub-field zones. Appropriate user-friendly models may help manage the underlying complexity in Eq. [10].

Careful analysis of the cost of adding better estimates for parameters in the N recommendation equation compared with the benefits in terms of improved estimates of N need should always be part of the process. Improvements in recommendations will be incremental, and we cannot wait until every parameter in an N recommendation equation is well described before we make use of modest improvements in recommendations through better parameter estimates. Farmers, the agricultural community, environmentalists, and citizens interested in our food system must be realistic about the uncertainty inherent in N recommendations; in humid environments rainfall will always create large uncertainties in the amount of N fertilizer needed by corn.

Several current methodologies discussed in this paper hold promise to better match in-season N applications with corn crop needs. They can generally be classified as improved approaches to predicting EONR before the growing season, or approaches that react to soil, crop, and weather conditions to fine-tune N rates during the growing season. Nitrogen rate prediction models, such as Adapt-N (Melkonian et al., 2008) and Maize-N (Setiyono et al., 2011) can incorporate localized soil properties, producer management, and weather conditions up to and during the growing season to provide refined predictions of EONR. In-season assessment of crop N status is a promising approach that can improve N use efficiency over some more traditional methods (Raun et al., 2002, 2005; Kitchen et al., 2010; Scharf et al., 2011). Systems using active crop canopy sensors rely on the growing plant to provide an estimate of N supply—from pre-plant fertilizer as well as soil-supplied N—up to the time of sensing. Such systems have the advantage of delaying the majority of N fertilization until just

before or during the period of rapid crop uptake of N, potentially reducing the exposure of fertilizer N to environmental loss. However, these systems rely on the accuracy of algorithms to convert crop reflectance in visible and near-infrared wavelengths to N rate recommendations. They also rely on the ability to apply N in a fairly narrow time window—generally from V6 to V12 for corn.

Increasing the accuracy of N recommendations and especially rate prediction models will require the development of methods to incorporate observed uncertainty in EONRs into recommendations and models. Economic optimal N rates have been used as important yardsticks for developing and improving yield goal recommendation systems and rate prediction models. The concept of EONRs also underlies the MRTN recommendation system (Sawyer et al., 2006).

One aspect of EONRs that is often overlooked and little studied is the effect of uncertainty in EONR values on the development of N recommendations and refining rate prediction models. The yield goal system does not provide an estimate of uncertainty of the EONR, and most rate prediction models do not provide an estimate of the uncertainty in their predictions. The MRTN system recognizes uncertainty in EONR by arbitrarily providing N rates within \$1.00 of the MRTN rate, and by providing graphs of the average N response (Fig. 7 and 10). Several past studies showed how the choice of functional forms or response models affects the uncertainty in EONR values for individual trials (Cerrato and Blackmer, 1990; Bullock and Bullock, 1994; Kyveryga et al., 2007).

There are only a few examples in the agronomic literature, however, where researchers estimated confidence intervals or confidence bands for EONR (Bachmaier and Gandorfer, 2009; Hernandez and Mulla, 2008; Jaynes, 2011; Sela et al., 2017). The results from these studies clearly show that large uncertainties exist around EONRs, and that confidence bands should be calculated to communicate the realistic precision of EONRs (Fig. 14). Factors that affected the size of confidence bands about EONRs included the choice of a model, how well the model fitted the observed data, and the variance of the yield response. Other factors thought to affect the width of the bands include the size of the plots used in the experiments, whether traditional small plot trials less than 50 m² in area or field-scale plots harvested with yield monitors, and the number of rates of N in the trials. Developing methods to include observed uncertainty in EONRs should be a priority area for research and will require large data sets of N response trials.

Historically, N recommendations have been based on N response trials that have generally been completed on small plots (<50 m²) and designed in isolation of other agronomists or soil scientists working across state boundaries or regions, even when the source of funding may be the same (Mitchell and Osmond, 2012). Recognizing the realities of funding, regional agricultural practices, and differences in agroecosystems, a basic experimental design should be developed, and perhaps minimum data reporting requirements, that would allow data to be easily analyzed across multiple sites, soils, and climates (Eagle et al., 2017). Developing this “standard” design with minimum data reporting requirements would require the inclusion of many N researchers across the country and much consultation. Besides including typical measurements of soil

and crop parameters influencing N use efficiency, such studies should also include detailed measurement of environmental factors, particularly soil water supply. In addition, the designs need to stipulate minimum plot sizes and replications, standard management practices, annual trial translocation to eliminate carry-over effects, etc.

Field-scale trials are also needed to validate N recommendations resulting from research performed on small plots. Standard designs and minimum data reporting requirements also would need to be developed for field-scale trials following the recommendations in Eagle et al. (2017). Farmers have taken advantage of yield monitors on combines to collaborate with scientists and other farmers in networks of farmers to perform field-scale evaluations of N rates and other agricultural practices as noted above. Integrated research that includes small-plot trials and field-scale trials across many agroecosystems

will be critical to further the science and improve N recommendations for corn. With the thousands of N rate trials conducted with corn over decades, and the N rate trials yet to be conducted, agronomists should be working toward providing farmers with recommendations based on evidence from trials combined over many years and locations similar to the MRTN system, but with more information provided about effects of soils, practices, and weather on the probability of the accuracy of the recommendations in an individual field or areas within fields.

Results from N rate trials, like medical research, are fraught with contradictory results. Evidence-based medicine is developed from numerous studies to integrate the best research available and has become the standard for medical journals (Sanchaya et al., 2010). The research is then used to generate guidelines to assist with decision making. Metadata analysis is the basis for the evidence that is then used to guide decisions.

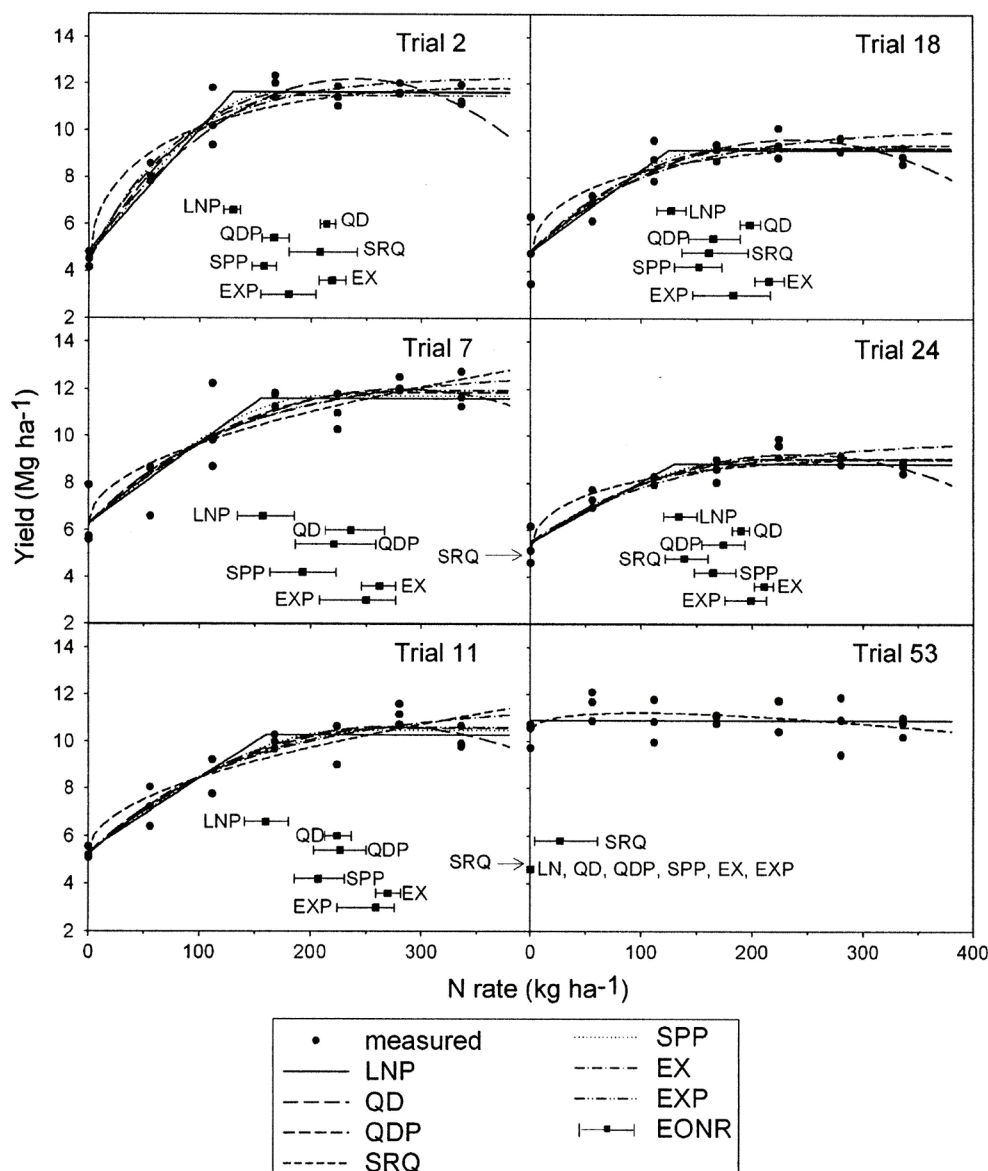


Fig. 14. Measured yields from six trials of Kyveryga et al. (2007) fitted with the seven yield response functions, namely, linear plateau (LP), quadratic (QD), quadratic plateau (QDP), square root quadratic (SRQ), spherical plateau (SPP), exponential (EX), and exponential plateau (EXP). Also shown are the computed economically optimal nitrogen rates (EONR) for each response function and their 68% confidence bands relative to the abscissa. The EONR for the SRQ function is beyond the scale used for Trials 7 and 11. For Trial 53, six of the seven functions reduced to the average yield when only significant terms in each function were retained, giving EONR values of 0 (no N response) (Jaynes, 2011).

The idea of metadata analysis is that several independent studies are combined on the same effect (N rates), and that the studies have treatment means that exceed the control means or vice versa (all the same direction of effects); in addition, standard deviations by treatment need to be available (Steel et al., 1997), and many observations are needed for drawing reliable conclusions because of the complexity of N response in agricultural fields (Olkin and Shaw, 1995). The analysis of the data also needs to provide farmers and farm advisors as well as policymakers the magnitude of the treatment effect and confidence in that magnitude (Olkin and Shaw, 1995), rather than the typical analysis of agricultural studies about whether a treatment effect was present or not. More reliable estimates of the magnitude of an effect of a treatment in agricultural fields can only be obtained by pooling data from large numbers of trials.

Some studies in agriculture have begun using metadata analysis of aggregated data and thus have begun evidence-based agricultural decision making. The advantages of meta-analysis for improving N recommendations in corn are shown in a study using data that estimated the effect of soil texture and weather on corn response to N (Tremblay et al., 2012). Many papers have been published about the effect of soil texture and weather on corn response to N, but often the conclusions are contradictory. Contradictory results are common in research reports about the response of corn to N, often because the number of locations and years where experiments were performed were insufficient to describe the variability in N response. The meta-analysis by Tremblay et al. (2012) combined 51 studies across seven states in the United States over 4 yr with a wide range of environmental conditions and soils. These data were sufficient to quantify the effect of soil texture and weather on corn response to N, which analysis of the individual studies was unable to reliably conclude.

Meta-analysis of individual plot data, which is called individual participant data in other scientific disciplines such as the medical and social sciences, provides a much richer and more robust analysis of research data compared with meta-analysis of aggregate data (Cooper and Patall, 2009). Creating N recommendations that provide the farmer or farm advisor with a reliable estimate of the probability that the recommendation will be accurate at the field or subfield level should be the goal of recommendation systems in the future. No N recommendation can be 100% accurate for an individual field or subfield. Many unknown and difficult to predict factors affect fertilizer N needs. Factors such as current crop and variety, seasonal rainfall patterns that vary in frequency and intensity across years, previous crop, soils, timing, form and placement of N, and interactions of these factors create the need to develop N recommendations in terms of probabilities of needing a certain rate of N given specific factors for an individual field. The fact that yield and response to N act independently also has to be considered (Raun et al., 2011). Providing recommendations as probabilities will enable farmers to make better decisions about N management and to attain the goal of N recommendations:— to accurately estimate the gap between the N provided by the soil and the N required by the plant.

We propose a method to create N recommendations that will enable continuous improvement of N use efficiency at the lowest cost. The method is the creation of data bases controlled

by farmers containing results from large numbers of field-scale, replicated strip trials evaluating N response or containing simply yields from fields or subfields with associated metadata about field history and N management practices. The databases would contain yields of individual plots or fields and subfields, and metadata that includes soil information, field history, cropping and N management practices, and growing season climate data. A database of replicated strip trials of a sufficient number of trials (the number is currently unknown, but without the collection of results from a large number of trials will remain unknown) would enable calculation of reliable probabilities for N recommendations across different environments, growth stages of corn, soils, and farmer practices (Kyveryga et al., 2013). A database of yields from fields or subfields would enable calculation of benchmark metrics for yield and N use efficiency for fields with similar soils, environmental conditions, and N management practices, which farmers would use in a continuous N management improvement programs (Cassman, 2017a). This process of benchmarking yields and N use efficiency could be less complicated and more efficient with the recent development of a technology extrapolation domain spatial framework (Cassman, 2017b) for the U.S. Corn Belt. Access to the technology extrapolation domain is available online on the NutrientStar web site (NutrientStar, 2017).

It is critical for full exploitation of these databases that agronomists from both the public and private sector find mechanisms to work as teams within and across agroecosystems and to include other research disciplines including, as a minimum, sociologists and economists. Most importantly, the scientists who develop the databases need to include farmers, agribusinesses, commodity and environmental organizations as partners in the development of the databases to create a foundation for continuous improvement of N recommendations. Collaborative development of databases is critical to ensure that new N-fertilizer decision tools and strategies can be adopted rapidly by farmers, while also allowing scientists from many disciplines to analyze the data to continuously improve the recommendations and to inform policy. As we move forward to improve N fertilizer recommendations, we must be mindful that two factors have profound effects on adoption rate—ease of use and cost to farmers—which often determine the acceptance of practices (Hoag et al., 2012). We must keep it practical and inexpensive to ensure that it is realistic for farmers to use on a routine basis.

We hope this review of what comprises a N recommendation, the science and assumptions underlying recommendations, and the science and assumptions underlying tests and models used to improve generalized recommendations, helps scientists, agricultural service providers, farm organizations, environmental groups, and others interested in food production and environmental quality understand the strengths and limitations of current N recommendations for corn.

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