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Algorithms for In-Season Nutrient Management in Cereals

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ABSTRACT

The demand for improved decision-making products for cereal production systems has placed added emphasis on using plant sensors in-season, and that incorporate real-time, site specific, growing environments. The objectives of this work were to describe validated in-season sensor-based algorithms presently being used in cereal grain production systems for improving nitrogen use efficiency (NUE) and cereal grain yields. A review of research programs in the central Great Plains that have developed sensor-based N recommendations for cereal crops was performed. Algorithms included multiple land-grant university, government, and industry programs. A common thread in this review is the use of active sensors, particularly those using the normalized difference vegetation index (NDVI) for quantifying differences in fertilized and non-fertilized areas, within a specific cropping season. In-season prediction of yield potential over different sites and years is possible using NDVI, planting date, sensing date, cumulative growing degree days (GDD), and rainfall. Other in-season environment-specific inputs have also been used. Early passive sensors have advanced to by-plant N fertilization using active NDVI and by-plant statistical properties. Most recently, sensor-based algorithm research has focused on the development of generalized mathematical models for determining optimal crop N application. The development and promotion of fee-based modeling approaches for nutrient management continues. Nonetheless, several algorithms using active sensors for in-season N management are available from state and government sources at no cost and that have been extensively field tested and can be modified by producers.

Core Ideas

- Normalized difference vegetation index algorithms can improve fertilizer N efficiency.
- Normalized difference vegetation index sensors currently sold employ these algorithms.
- Algorithms rely on knowledge that increased yields increase fertilizer N demand.
- Yield potential and N response are independent.
- Nitrogen-rich strips help to predict in-season grain yields.

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Over application of N fertilizer in cereal production systems continues to be problematic (Biello, 2008). The environmental costs of over applying fertilizer N are highlighted by iconic examples of hypoxia in the Gulf of Mexico and Chesapeake Bay (Ribaudo et al., 2011). This work further noted that N applied at rates that exceed crop needs has a greater risk of leaving the field and degrading water supplies. For Iowa (largest tonnage of fertilizer N purchased and applied in the United States), this has become somewhat uncomfortable as within-state lawsuits have been filed against maize (*Zea mays* L.) producers surrounding the Des Moines and Raccoon rivers for over applying N (Charles, 2015). Solutions exist but involve practices that will require a significant investment in equipment and management (Roberts et al., 2012).

Use of sensors in agriculture has advanced from measuring transpiration rates in 1917 (Briggs and Shantz, 1917) to on-the-go sensing and application of fertilizer on a by-plant scale (Kelly et al., 2015). Other work has suggested that the highest precision in N management for maize can be achieved through in-season N applications that are based on early-season N dynamics using models that dynamically simulate soil and crop processes (van Es et al., 2007).

The adoption of sensor-based nutrient management has been slow, but consistent with the delayed adoption of other agricultural technologies (Fuglie and Kascak, 2015). This work further noted that diffusion of new agricultural technologies improved with increased farm size and producer education.

Work by Holland and Schepers (2010) reports a function that delivers N fertilizer recommendations based on in-season remote sensing and local production information. Solie et al. (2012) developed a methodology using a sensor-based approach that is applicable for both wheat (*Triticum aestivum* L.) and maize, and that works over different stages of growth. Even so, both of these approaches rely on in-season measurements of a growing crop canopy.

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Abbreviations: EONR, economic optimum nitrogen rate; GDD, growing degree days; NDVI, normalized difference vegetation index; NUE, nitrogen use efficiency; OSU, Oklahoma State University; RI, response index.

YIELD AND ENVIRONMENT INFLUENCE NITROGEN DEMAND

Noteworthy in the literature is that as yield levels increase, the demand for increased nutrients also increases (Ciampitti and Vyn, 2014; Fowler, 2003). Spiertz and DeVos (1983) noted that an accurate assessment of the potential yield level for different growing conditions would improve the recommendations and optimize use of N fertilizers. Mullen et al. (2003) found that in-season computation of N response using NDVI measurements, identified those environments that would respond to additional N, and noted where increased N uptake was expected. This work further reported that N response was highly variable over sites and years. Shanahan et al. (2008) hypothesized that visual appraisals of crop N response (N Reference, or N Ramps) were tools that could entice farmers into being involved, and that would encourage them to think about agronomic principles relative to their N management. This work also reported that farmer adoption of these new approaches will likely be accelerated as they are embedded within a strategy that provides positive visual feedback.

Scharf et al. (2011) reported that sensor-based N applications represented a reduction of approximately 25% in the amount of N applied beyond what was removed in the grain. Their results showed that sensors can quantify N rates for maize that perform better than those directed by producers. Arnall et al. (2009) observed temporal variability in NUE and further noted that NUE could be predicted, but that it was site-specific. Added site-to-site variability was reported by Bundy and Andraski (2004) who showed that the economic optimum nitrogen rate (EONR) varied dramatically, ranging from 0 to 168 kg N/ha over 21 winter wheat locations.

Work by Lory and Scharf (2003) with maize noted that fertilizer recommendation systems that ignore yield are limited to explaining <50% of the variation in optimum N rates, highlighting the importance of projecting crop N removal. Field experiments conducted throughout Oklahoma (Mullen et al., 2003) showed that in-season N demand for added N fertilizer in winter wheat could be detected using NDVI readings collected at Feekes growth stage 5 (Large, 1954). This was advanced from earlier findings where early-season NDVI readings were used to predict yield potential, and later employed to refine in-season fertilizer N rate recommendations (Raun et al., 2001). Similar work by Varvel et al. (1997) showed that early-season maize N deficiencies could be corrected using chlorophyll meter readings and a sufficiency index approach.

The objective of this paper was to describe validated in-season sensor-based algorithms presently being used in cereal grain production systems for improving NUE and grain yields.

MATERIALS AND METHODS

Research programs in the central Great Plains that have developed sensor-based N recommendations for cereal crops were targeted to provide an outline and justification for in-season sensor-based algorithms widely used for maize and wheat. These embodied algorithms were generated by multiple entities coming from land grant universities and government programs that were recognized, published, and well known in the crop sensor discipline.

Active-sensor research programs participating in the annual Nitrogen Use Efficiency Workshop (most recently held in Auburn, AL, August 2015) were asked to provide a summary/synopsis of the sensor-based N rate algorithms developed for their regions over the years and that could be included in a joint manuscript. Several of the published in-season sensor-based N algorithms and associated summaries developed from each group were thus included.

RESULTS

Holland–Schepers

The Holland–Schepers algorithm is based on the shape of a typical N rate by yield response function (quadratic or quadratic plateau)(Holland and Schepers, 2010). The quadratic portion of the function near maximum yield is particularly important because producers strive to achieve near maximum yield with the least amount of N fertilizer. Active crop canopy sensors are unable to quantify the amount of excess N in plants, so for in-season N management to be effective, producers should expect parts of a field to show less than adequate vigor and greenness at the time of sensing. It is important that maize plants are not exposed to stresses during the V5 to V7 growth stages. This may require more modest pre-plant N to avoid early season N stress. Excess pre-plant soil N availability (>25–30% of the total N uptake) will delay the growth stage at which the crop becomes sensitive to N status and could be problematic unless high-clearance applicators are available. Plant N uptake for maize is rapid between V6 and silking and from Feekes 4 until heading for wheat. Evidence of N deficiency during these periods depends on the amount of pre-plant N application, residual soil N, or N credits. Because N stress can be subtle and visually difficult to quantify, it is important that plants with adequate N within the field be identified as a reference. The soil N supply required to meet the "adequate N" criteria increases from about 20% of the total crop N uptake at V6 to about 70% at silking. A so-called high-N reference that equates to a modest excess above the producer's typical N rate is unnecessary and can reduce early season vigor by inducing a nutrient imbalance as with S. As such, establishing a N-rich strip as a reference for the purpose of calibrating active sensors can be problematic (Schepers and Holland, 2012).

The anchor of the Holland–Schepers algorithm is a term called Nopt, which is the optimum N rate provided by producers. The EONR can be substituted for Nopt if it is known. The N_{opt} value is reduced by N credits as appropriate. It is important to note that at the time of sensing, plants have already responded to some N credits like early season mineralization following soybean [*Glycine max* (L.) Merr.], but is also affected by N losses (leaching or denitrification) or N immobilization following incorporation of high C residues (maize stalks or wheat stubble). It should be noted that Nopt embeds producer experiences and field-specific considerations, including previous yield levels (i.e., realistic yield goal).

The active sensor component of the algorithm has its base in how the adequately fertilized reference value is established. Rather than contending with the uncertainties associated with a high-N reference strip, the Holland–Schepers algorithm uses a statistical approach (frequency distribution or cumulative percentile) that identifies plants in the more fertile parts of a field strip or two to characterize plants with adequate N

(Holland and Schepers, 2011, 2012). Hence, this approach minimizes the potential for nutrient imbalances caused by excess N availability. For example, a growing database shows that when the leaf N/S (sulfur) ratio exceeds 15:1 (10:1 to 12:1 is optimum for maize) new leaves are likely to display yellow streaks and even reduced biomass. As such, caution should be exercised when establishing N-rich strips (i.e., make sure that S is not limiting because it is soluble and leachable) because high soil N availability relative to S can result in artificially low reference vegetation index values and low fertilizer N recommendations. The approach is termed a "virtual reference" because it identifies adequately fertilized plants whose reflectance serves as a reference from which a sufficiency index (SI) is calculated. The virtual reference approach to sensor calibration is far less likely to generate erroneous N recommendations than the N-rich approach because less than half as much N is applied pre-plant that could upset the N/S balance.

The virtual reference procedure involves driving through a part of the field that includes nearly the full range in plant vigor. The software extracts the 95-percentile value from a histogram of the sensor's vegetation index values. All vegetation index values are divided by the reference value to generate a SI that characterizes the relative degree of N stress. Experience indicates that SI values <0.7 are not likely to achieve expected yields even if adequate N is applied and so the algorithm allows producers to select the rate at which the N rate is reduced (fast, medium, slow). Finally, the algorithm compensates for N that is already accumulated in the crop at the time of sensing and includes an overall coefficient that allows producers to compensate for management zone differences.

Most active sensor-based algorithms use a calibration method similar to the one set forth by Peterson et al. (1993) that was developed for Minolta SPAD chlorophyll meters. The premise behind the SI or RI calibration procedure was that the reference crop was similar in all respects except for the N status. Implied was the assumption that other nutrients were adequate to achieve near maximum yields. In the case of crop canopy sensors, vegetation index values are used instead of SPAD meter values to calculate SI. Some algorithms prefer to invert SI to generate a response index (RI), which is a nonlinear parameter. In either case, the concept is simple and straightforward. The SI values characterize relative photosynthesis within the field at the time of in-season sensing. Integrating photosynthetic activity over the growing season culminates with grain production and yield (Holland et al., 2012). In-season SI values at V9 and V12 have been shown to be highly correlated (r^2 = 0.9 or greater) with relative yield (Schepers and Holland, 2012). The premise is that if relative crop vigor (plant chlorophyll content and biomass, which is a proxy for plant N status) can be remotely quantified during the growing season, an appropriate amount of N fertilizer can be applied to recover the potentially lost yield. Nonetheless, severe early-N stress has been shown to decrease final grain yields even when mid-season N was applied (Scharf et al., 2002).

The Holland–Schepers algorithm was extensively evaluated in replicated field studies in 2008 and 2009 before being incorporated into the AgLeader OptRx system for making in-season N applications. It follows that the algorithm is used in the United States and internationally wherever OptRx sensors are used on maize, wheat, potato, etc.

University of Missouri/USDA-ARS

Early Missouri maize investigations using near-crop passive light reflectance sensing demonstrated good relationships between the reflectance measurements and EONR (Scharf and Lory, 2009). Results from this work were the basis of N recommendation algorithms developed for both the GreenSeeker 505 and Holland Scientific ACS-210 sensors, with specific versions published by Scharf et al. (2011). While other canopy-sensing algorithm development for maize has been based on NDVI, these early Missouri studies indicated excellent sensitivity to plant N condition using the inverse of the simple ratio (ISR), an index that is the ratio of visible reflectance to near infrared (NIR) reflectance. This ratio was also selected because it placed emphasis on the visible measurement, since many visible wavelengths were sensitive to plant N status, but NIR alone was not (Scharf and Lory, 2009). It should be noted that ISR index values decrease with increased plant growth, while NDVI increases with plant growth. This inverse relationship has been illustrated (Kitchen et al., 2010; Sheridan et al., 2012).

The developed Missouri algorithms are dependent on the relative reflectance from unfertilized maize (called target) to sufficient-N maize (called N-sufficient reference). In principle this has proven successful in many spectral measurement investigations. In effect, the greater the difference in sensor reflectance measurements between unfertilized maize and N-sufficient reference maize, the more N fertilizer need. Without this reference to determine a relative difference, there is little basis for making N rate recommendations. As such, producers using this technology with Missouri algorithms are instructed to fertilize an area or "strip" within a field before or shortly after planting so that N is not limiting up to the time of reflectance sensing. When fields have a high degree of within-field soil variability, producers are encouraged to consider multiple N-sufficient areas for highly contrasting soils. Additionally, these N-sufficient reference areas should avoid areas that are unique or historically have had other management problems (e.g., heavy weed infestation, head-lands with soil compaction, terraces, manure history). While different maize hybrids can have an effect on reflectance measurements of N-sufficient plants, the impact is minimal and will not greatly impact algorithm N rate recommendations (Sheridan et al., 2012). However, experience working with producers has demonstrated that other soil and crop management factors may cause variations in reflectance, so producers are encouraged to have a sufficient-N reference area for each field. Experience on producers' fields with poor plant stands, even in a small portion of the sufficient-N reference area, will likely result in underestimation of N maize requirements. To guard against this happening, upper ISR values as a function of growth stage for the sufficient-N reference is recommended (Sheridan et al., 2012).

The Missouri N rate algorithms for maize were constructed using the ratio of the ISR of the target plants to the ISR of high-N plants, referred to as the relative ISR (Scharf et al., 2011). Since ISR values of unfertilized target maize will be equal or greater than ISR values of sufficient-N reference maize, relative ISR values produce a value ^{3}1.0. This value could be considered a RI like that described previously. Additional Missouri investigations found relative ISR values were different with the two different canopy sensor types and maize growth stage. Therefore, sensors-specific algorithms were produced for maize at three vegetative V6–V7, V8–V10, and V11–V16 growth stages (Scharf et al., 2011). The effect of the different growth-stage algorithms for a single relative ISR value is that the N fertilizer recommended decreases with advancing growth stage. A feature of the Missouri algorithms is that N fertilizer will be recommended even when the relative ISR value is equal to 1.0. Foundational studies in Missouri demonstrated that maize plants that signaled no N stress during mid-vegetative growth stages often respond to in-season N fertilization. As such, an N fertilizer recommendation "floor" is built into the algorithms. As an example, when the GreenSeeker 505 reflectance produces a relative ISR = 1, N recommendation for V6 and V11 growth stage maize will be 55 and 35 kg N ha^{-1}, respectively.

Moderate success has been found when employing canopy sensing using the Missouri algorithms. Testing of canopy sensor-based N application on producer fields was initiated in 2004 with N rate trials to examine sensor/algorithm performance against EONR (Kitchen et al., 2010). With 50% of fields tested, within-field spatial variability in EONR was highly correlated with canopy sensing. Depending on soil type, fertilizer cost, and maize price, canopy sensing could provide increased profit US\$25 to \$50 ha^{-1}. A significant finding of this research was that this correlation varied by general soil characteristics, such as soil organic matter and texture. Performance of the algorithms could possibly be improved by including these variables. Other side-by-side strip trials on producers' fields compared sensor/algorithm performance with a fixed producer rate and found an average partial profit of \$42 ha^{-1}, while using 16 kg ha^{-1} less N (Scharf et al., 2011).

North Dakota State University

The North Dakota State University maize algorithms (Franzen et al., 2014) were developed using more than 60 field N-rate trials across North Dakota, recording active-optical sensor readings from the Holland Scientific Crop Circle sensor (red- and red-edge-NDVI) and the GreenSeeker (red- and red-edge-NDVI). The foundation for the algorithms embeds the In Season Estimated Yield (INSEY) concept developed at Oklahoma State University. However, instead of using the RI approach (Arnall et al., 2006), algorithms were separated into surface soil textures, regions within North Dakota, and tillage categories found important in N response curves during the study. Regions were separated into fields East of the Missouri River and those West of the river. Tillage encumbered categories that were either long-term no-till (6 yr of more continuous no-till/strip-till) and anything else categorized as conventional tillage. Textures East of the Missouri River were categorized as high clay (soils with clay content >400 mg kg^{-1}) and any other textures, classified as medium texture.

The algorithms were based on establishing in-field N-nonlimiting areas at or before planting. The in-field N-nonlimiting area was necessary due to the frequency of S deficiency in the region. If a virtual reference area was utilized and S deficiency was present, the virtual reference area (the greenest area in the field) could have had the lowest available N, because higher N results in greater expression of S deficiency in maize and other crops. Deficiencies of other nutrients are best detected and corrected using established soil testing programs.

Active NDVI sensor readings are related to maize yield. Grain yield predicted using INSEY from the N-non limiting area was the highest yield possible within a specific soil/tillage category and variety. If INSEY outside the N-non limiting area was within 5% of INSEY from the N-non limiting area, then in-season N was not necessary. If INSEY was more than 5% less than that of the N-nonlimiting area, then the yield difference using the algorithm was calculated by the controller, and N content of the maize yield difference was calculated. This result was then divided by an in-season N application efficiency factor defaulted at 60% unless adjusted by the applicator, and thus resulting in a predicted N rate to be applied. This method can be adapted to on-the-go N fertilizer applicator controllers with proper programming.

This algorithm is also simple enough that growers could utilize their own field N sensor readings and yield results to modify the algorithm over time so as to individualize by-field algorithms. To do so, growers could withhold N fertilizer from being applied in a given field pass, but continue to record sensor readings. At harvest, the combine monitor recorded yield data for all strips so that vegetation index readings could be related to yield within each strip. That relationship was merged with a weighted algorithm and over fields it morphed into one more characteristic for specific grower N response.

The NDSU algorithm also has a minimum INSEY. If INSEY was at or below a specific minimum, it was likely low because of a low plant population, or higher salt, or something unrelated to N nutrition. The fertilizer applicator would in turn not apply N when INSEY was at or below that value.

Oklahoma State University

Early work at Oklahoma State University (OSU) recognized positive correlation between passive NDVI measurements and plant biomass (Stone et al., 1996). This work went further to identify that these NDVI values were correlated with N uptake, by site, and by year. Their work further embraced the need to develop a system that worked over growth stages, sites, and crops (Raun et al., 2005). Simultaneous work from this group targeted the resolution where differences in soil test and yield parameters existed, so as to match sensing and sampling scales. Their work showed that significant differences in soil test parameters were found when samples were less than 1 m apart (Raun et al., 1998; Solie et al., 1999). Because of the small-scale variability found, sensor based management decisions were then evaluated using a 1-m^2 resolution (Thomason et al., 2002). This work showed that using an in-season sensor-based N algorithm, NUEs could be increased dramatically, but that required recognition of small-scale variability. Hodgen et al. (2005) showed that NDVI sensor values from a pre-plant N-rich strip divided by the NDVI reading from the farmer practice (termed the RI) were needed to estimate potential N responsiveness, by site and within a growing environment. A consolidated approach encumbering in-season yield prediction (Raun et al., 2001) and the RI, was later reported by Raun et al. (2002). This work went further to develop INSEY where NDVI was divided by a site-specific climatological input, and that allowed combining sites and years. The divisor was days from planting to sensing where growing degree days (GDD) > 0 [GDD =$(T_{min} + T_{max})/2 - 4.4$°C, where T_{min} and

T_{max} represent daily ambient low and high temperatures]. The INSEY index provided an estimate of rate of plant N assimilated per day (Raun et al., 2002).

This INSEY-RI algorithm embodied knowledge that yield potential (YP0) is independent of RI (Raun et al., 2010; Arnall et al., 2013) and that independent estimates of each are needed to arrive at reliable in-season sensor-based N rate recommendations. Logistics of this algorithm were that the predicted achievable yield potential if N was applied (YPN), was determined by multiplying YP0 by RI (YP0×RI approach). The difference in grain N uptake between YPN and YP0 was then divided by an expected efficiency to arrive at the in-season fertilizer N rate recommendation. This further employed the use of locally known values for grain N (Mosse, 1990) and/or documented by commercial laboratories within specific states and/or regions. A premise of in-season sensor based N recommendations is that spring and/or foliar applied N applications generally have higher NUE's (Sowers et al., 1994). Using by-site knowledge and in-season visual observations, this value can be adjusted accordingly by the producer.

Their work went further to encumber within plot spatial variability, estimated using the coefficient of variation (CV) from within-plot sensor readings (Raun et al. (2002) and Arnall et al., 2006). This is possible with the GreenSeeker NDVI sensor where more than 70 readings/m^2 are collected walking 5 km per hour.

Ortiz-Monasterio and Raun (2007) showed increased farmer profits in the Yaqui Valley, Mexico where the YP0×RI approach applied 69 kg N/ha less than the farmer practice, while producing the same level of grain yield. Similarly, the use of combined midseason sensor-based predictions of YP0 and RI provided accurate N rate recommendations when compared with flat rates in a rice production system (Tubaña et al., 2008).

DISCUSSION/SUMMARY

The earliest formal reporting for using a passive sensor to estimate the NDVI was in 1974 (Rouse et al., 1974). This work recognized that healthy vegetation absorbs most of the light in certain visible wavebands and reflects a large portion of the near-infrared light. The use of NDVI has also had roots with assessing environmental quality (Fung and Siu, 2000), forage biomass prediction (Freeman et al., 2007), and sensor based algorithms for N recommendations (Lukina et al., 2001).

Prevalent in this review was the use of active sensors, particularly NDVI, and chlorophyll meters for detecting differences in the vigor for plants receiving various fertilizer N application rates within a specific cropping season (Holland and Schepers, 2010; Raun et al., 2001; Scharf et al., 2011; Tubaña et al., 2012; Varvel et al., 1997). In-season prediction of yield potential over different sites and years has also been shown using NDVI, planting date, sensing date, and cumulative growing-degree days (GDD)(Raun et al., 2001; Girma et al., 2006). Furthermore, other in-season environment-specific inputs have been used including precipitation (Solari et al., 2008; Bushong et al., 2015). Early work using passive sensors led to the development of active sensors that advanced the potential for on-the-go, by-plant N fertilization using NDVI and small-scale statistical properties generated from NDVI sensor readings (Arnall et al., 2006). This review recognizes that the ongoing success of in-season based N recommendations will hinge on whether or not farmers can obtain a return on their investment, the amount of government support/incentives and the complexity of the system as a whole. It is important to note that several of the current commercial N management programs fail to address sensor-based and/or remote-sensing based in-season N management, likely needed to address worldwide cereal N use efficiencies that hover near 33% (Raun and Johnson, 1999).

Future active sensing platforms will likely offer enhanced usability with respect to calibration and decision support and subsequent transparency to the operator. As such, the user's cultural farming practice will be minimally impacted further easing adoption barriers. New N algorithms will likely incorporate specific seed genetic information and field-scale climate information. Also, real-time telematics will allow easy and seamless integration of new model information (soil, regulatory, economic, genetic, etc.) into a producer's variable rate technology (VRT) system while use of multispectral sensing systems or multi-sensor systems will help tune N application by simultaneously sensing water and nutrient status of the crop as well as landscape position and soil composition. Key differences in the in-season algorithms that should be considered by policymakers, farm managers, consultants, and producers are the way individual sensors are calibrated (i.e., establishment of crop reference values) and the sensitivity of specific wavebands relative to growth stage. The later point is critical because a lack of sensitivity to crop vigor can result in a false sense of security and lost profit. As such, producers are encouraged to select an approach that fits the spatial and temporal aspects of their fields and production systems.

A cautionary note must be added that re-emphasizes the continued need for comprehensive soil testing. The understanding of macro- and micronutrient deficiencies and their potential interactions is compulsory to making any decision for N alone. Nonetheless, this review reports on viable options for in-season sensor-based N methods, all of which have been documented to work with maize and wheat producers and that can decrease N loading rates in cereal crop production. Wide-scale adoption is at some point expected as sensor groups come together with more unified algorithms that state and government programs can endorse.

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