DEVELOPING NITROGEN ALGORITHMS FOR CORN PRODUCTION USING OPTICAL SENSORS

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ABSTRACT

Remote sensing for nitrogen management in cereal crops has been an intensive research area due to environmental concerns and economic realities of today's agronomic system. In the search for improved nitrogen rate decisions, what approach is most often taken and are those approaches justified through scientific investigation? The objective of this presentation is to educate decision makers on how these algorithms are developed and evaluate how well they work in the field on a small-plot basis. A single approach for algorithm development will be discussed to allow individuals to experience what a researcher considers when constructing an algorithm. This particular presentation will ignore the spatial variability aspect of nitrogen management and focus primarily on temporal variability and the management of nitrogen from year to year and location to location. Several key algorithm components will be discussed including yield prediction, identifying in-season responsiveness, and ultimately deciding on a fertilizer rate. Finally, research results will be shared to show how well a single algorithm performs across a wide array of production environments.

Keywords: nitrogen, algorithms, optical sensing

INTRODUCTION

Improving the nitrogen use efficiency (NUE) of agricultural production systems has been an intense area or research in recent years. Current NUE of cereal crop production is estimated to be near 33% worldwide (Raun and Johnson, 1999). This implies that 67% of the N applied for cereal crop production is not in the harvested grain and may be susceptible to loss which can negatively affect the environment. With the development of advanced optical sensing technologies and improvements in fluid delivery systems (specifically variable rate applications), sensor based N algorithms have been developed. To utilize in-season optical sensing tools, sidedress application of N is necessary which can potentially expand application of liquid N products.

A reference strip has been proposed as an appropriate way to identify crop response to N and provide a calibration point to determine N response (Peterson et al., 1993; Johnson and Raun, 2003; Schepers and Meisinger, 1994) on a field basis. Many studies have documented that N response is spatially and temporally variable and that yield response to added N changes dramatically (Bundy et al., 1999; Johnson and Raun, 2003). Mineralization of the N fraction of the soil organic matter is identified as the primary cause of variable N response (Johnson and Raun, 2003). Unfortunately, predicting mineralization rates of organic matter has proven to be difficult because mineralization is controlled by unpredictable environmental conditions. The N reference strip allows the opportunity to identify if response to additional N is likely. Previous work in winter wheat (*Triticum aestivum*, L.) has shown that in-season estimates of the response index (RI_{NDVI}) using optical sensors is highly correlated with the response index measured at harvest ($RI_{Harvest}$) (Mullen et al., 2003). Similarly, work in corn (*Zea mays*, L.) has shown that N response measured at various stages of growth (V6-R3) (Ritchie et al., 1997) with a SPAD meter is indicative of N response observed at harvest (Varvel et al., 1997).

Active optical sensors have also been used to develop N algorithms in corn (Raun et al., 2003). The use of the reference strip remains, but instead of using the sufficiency index (SI) to compute responsiveness, RI is calculated (RI is simply the reciprocal of SI). The RI determined for a specific environment, from sensor readings (NDVI), is used as a multiplier to adjust N recommendations based on variations in yield potential (Raun et al., 2002). As sensor readings are collected, at a defined resolution which is correlated to yield potential, N recommendations are changed based on yield potential and site responsiveness.

The objective of this article and subsequent presentation is to delineate a single, yield-goal based algorithm and discuss the components included to make a N rate decision.

YIELD PREDICTION

The first component of a yield-goal based algorithm is a yield prediction model based upon in-season optical sensor measurements. There are many different vegetative indices that can be utilized including normalized difference vegetative index (NDVI – including red, green, amber, etc), visible vegetative index (red, green, amber, etc.), and simple ratio (SR – visible divided by near-infrared). Active sensors (sensors that utilize their own light source independent of sunlight) are currently available to measure NDVI, SR, or individual reflectance values from individual wavebands. Oklahoma State and Virginia Tech utilize NDVI in their yield prediction model for winter wheat and corn. In addition to the vegetative index, Oklahoma State proposed an environmental factor be included to allow multiple locations to be placed on the same graph for predicting grain yield. Originally, days after planting (DAP) was utilized to calculate an in-season estimate of yield (INSEY) value by dividing NDVI by DAP (reference). Including corn data from Ohio with the Oklahoma State yield prediction model (using DAP as the environmental component) reveals that despite the different geographic regions, the yield prediction curves are similar (Figure 1).

Despite the relatively good correlation between INSEY and final grain yield, there are a considerable number of data points that reside below the exponential line that defines the relationship. This should not be a surprising phenomenon considering anything can occur after in-season measurements are made around V8 to V10 growth stage corn (Ritchie et al., 1997) that can reduce corn grain yield. More importantly, very few data points are above and to the right (for SR INSEY model – Figure 2) of the exponential equation revealing that the yield prediction model can identify the upper end of yield potential if optimum conditions continue throughout the growing season. Therefore an additional line was fit to the model to represent this upper bound (Raun et al., 2005). This upper bound is one standard deviation above the trend line, and this is the line used for yield prediction in the algorithm.

IN-SEASON PREDICTION OF NITROGEN RESPONSE

Yield prediction is a key component of a yield-goal based algorithm, but it is meaningless in the absence of some measurement of the likelihood of nitrogen response. Multiple publications have recently revealed that yield prediction alone (whether in-season or prior to planting that has historically been used) is a very poor predictor of the amount of nitrogen that needs to be supplied by fertilization (Sawyer et al., 2006).

Originally, the work in winter wheat showed that NDVI measurements taken from a target plot (plot that received a relatively low amount of nitrogen fertilizer) and a reference plot (plot that had received more than adequate nitrogen fertilizer) could be used to calculate an in-season response index. This response index measured in-season was then correlated with post-harvest response using grain yield (Mullen et al., 2003). For winter wheat NDVI based response index worked well, but for corn the NDVI methodology may not be the most appropriate especially if starter N is used.

In-season estimates (NDVI based) of response using plots that have received starter or planter nitrogen are not as well correlated with post-harvest response when compared to plots that did not receive any nitrogen (Figure 3). One possible explanation for this poorer correlation between in-season and post-harvest response when starter nitrogen is supplied could be that the responsiveness of the crop is masked at the time of sensing due to the timing of the measurement. In-season optical sensor measurements are proposed to occur near V8 growth stage. This is a time when the crop has not necessarily taken up much nitrogen (Mengel, 1995). Thus supplementation with a small amount of nitrogen may be masking the true responsiveness of the crop.

Instead of using NDVI to measure crop responsiveness, SR could be used to measure response index (Figure 4). Utilizing SR to determine response index results in a slightly better correlation than NDVI, but interestingly, using SR shows little difference between RI measured using a check plot or a plot that received some nitrogen fertilizer early (the linear relationships are similar).

In-season response can be measured using optical sensors, but a reference or non-limiting nitrogen strip must be established to calculate this estimate. It could be argued that a check strip should also be used with a reference strip to determine in-season responsiveness.

COMBINING COMPONENTS TO MAKE A FUNCTIONAL ALGORITHM

The two major components for building an optical sensor based nitrogen algorithm are in place, now the components must be assembled. Starting with the yield prediction model, based upon sensor readings from the reference plot, an estimate of yield can be calculated. Assuming a SR value of 0.23 and 60 days after planting, the estimated yield of the target (area that will receive fertilization) would be:

$$20.13 \exp^{-0.065*(0.23*52)} = 8.21 Mg/ha$$

This estimated yield is the yield potential without any additional nitrogen fertilizer. Now the response index is calculated to determine how responsive a particular site is. Response index SR is calculated using the following equation:

RI-SR = reference SR / target (or check) SR

For this example assume the target SR is 0.23 and the reference SR is 0.20. The RI-SR is 0.87. This value needs to be corrected since the linear relationship between RI-SR and RI-harvest has a slope different than one and an intercept greater than zero. The actual RI-SR used in the algorithm utilizing the non-check (target-40) adjustment would be:

RI-SR = -(1.97 * (SR-reference/SR-target) + 3.1744) = 1.43

with an upper limit set such that the ratio SR-reference/SR-target is not larger than 1. Now a new value can be computed to determine, the potential yield based upon the initial estimated yield of the target and the responsiveness of the site to additional fertilizer. This value is known as the potential with additional nitrogen fertilization (YPN). It is calculated using the following equation:

YPN = 8.21 Mg/ha * 1.43 = 11.74 Mg/ha

Now a determination must be made as to how much nitrogen fertilizer to supplement. This is calculated by determining the difference in nitrogen uptake between YPN and the original estimated yield. Assuming that grain nitrogen concentration (1.3%) is a constant we can determine the uptake amount of both yield estimates. The difference in nitrogen uptake would be:

N-difference (kg/ha) = (11.74 Mg/ha*0.013*1000) - (8.21 Mg/ha*0.013*1000) = 46

Another component is still needed, since one hundred percent utilization efficiency of supplied nitrogen is improbable another adjustment must be made to determine the actual nitrogen recommendation. At present an assumption of 60% utilization efficiency is used. So the actual nitrogen recommendation would be:

Nitrogen recommendation (kg/ha) = 46/0.60 = 77

EVALUATING THE ALGORITHM

The algorithm should then be evaluated to determine how well it does at actually recommending nitrogen using empirical data. For this analysis, three locations will be utilized. The locations were all nitrogen rate studies conducted in Ohio where sidedress applied nitrogen was supplied the day of or after sensor measurements were made from the target, check, and reference areas. A nitrogen response curve was determined for each experimental location, and the algorithm derived nitrogen recommendation was compared to the empirical optimum nitrogen rate. At all three locations, the algorithm performed relatively well with some expected deviation from the empirical optimum nitrogen rate based upon the nitrogen response curve (Table 1). At the Northwest location, both algorithms performed similarly because the difference in SR between the target and check plots were similar. Using the RI-SR (40) algorithm at the Western locations resulted in a large over-recommendation of nitrogen, but the RI-SR (0) did make as large an error. Finally, at the Wooster the RI-SR (40) algorithm recommended close to the agronomic optimum nitrogen rate, but the RI-SR (0) algorithm over recommended nitrogen.

While an algorithm has been developed, work continues on how to adjust the final two components (grain nitrogen concentration and nitrogen utilization efficiency) to improve the performance of the algorithm.

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Table 1. Empirical agronomic optimum nitrogen rate based on nitrogen response data, SR-based algorithm using 40 for calculation of response index, and SR-based algorithm using the check for calculation of response index at three locations in Ohio, 2007.

Location	Agronomic optimum nitrogen rate	RI-SR (40) recommended rate	RI-SR (0) recommended rate
	----------------------------kg/ha	--------------------------------	
Northwest	81	84	71
Western	0	104	41
Wooster	137	142	173

Figure 1. Relationship between INSEY using NDVI and final corn grain yield from four locations in Ohio and the Oklahoma State University yield prediction model.

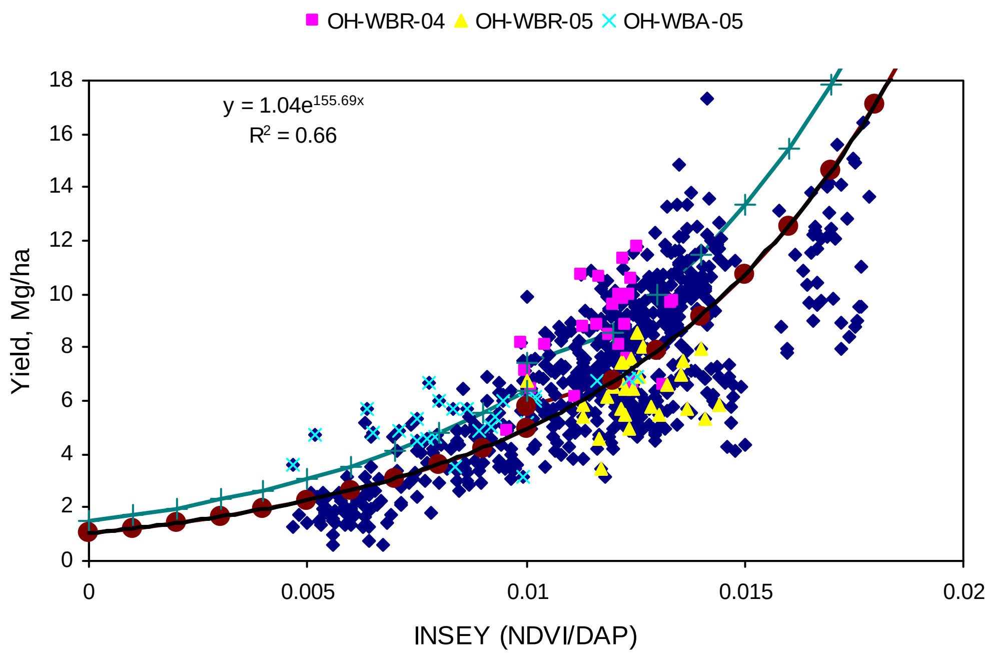

Figure 2. Relationship between INSEY using SR and final corn grain yield from four locations in Ohio and the Oklahoma State University yield prediction model.

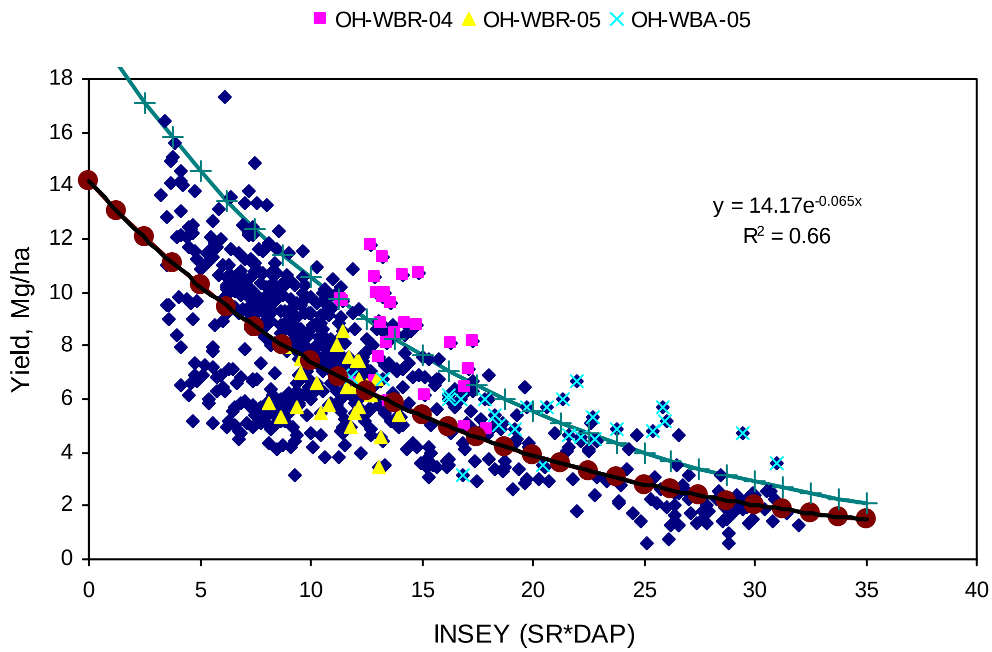

Figure 3. Correlation between in-season NDVI response index and post-harvest response index at 17 locations.

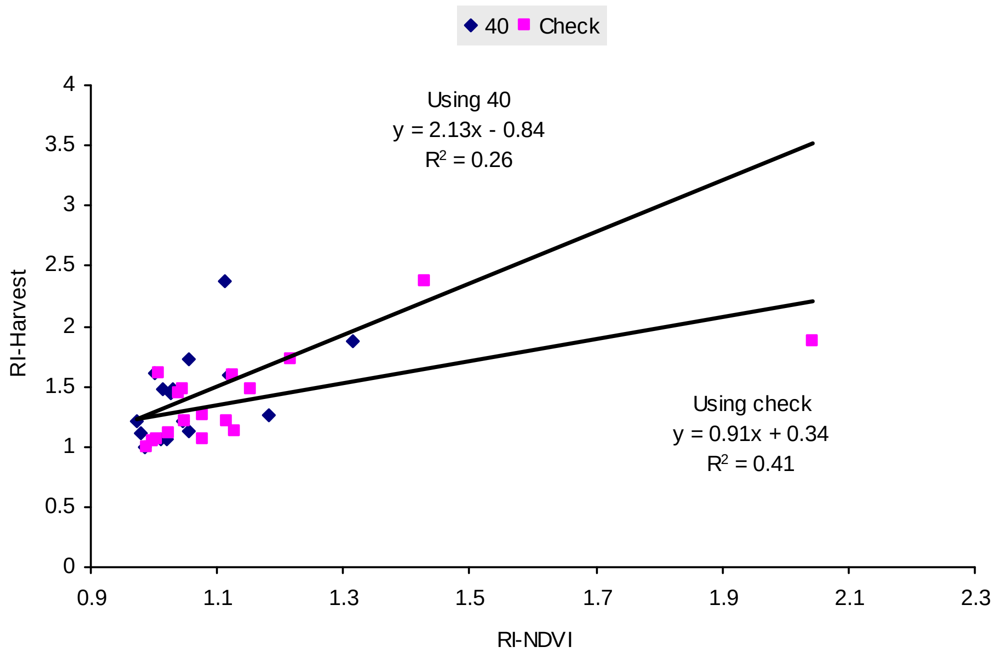

Figure 4. Correlation between in-season SR response index and post-harvest response index at 17 locations.