Canopy Sensing Algorithm Performance and Modification

Using Soil and Weather Information

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By

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The undersigned, appointed by the dean of the Graduate School,

Have examined the Thesis entitled

CANOPY SENSOR ALGORITHM PERFORMANCE AND MODIFICATION

USING SOIL AND WEATHER INFORMATION

Presented by G. Mac Bean

A candidate for the degree of

Masters of Science

And hereby certify that, in their opinion, it is worthy of acceptance.

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Dr. Newell Kitchen

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Dr. Randall Miles

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Dr. Richard Ferguson

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Dr. Peter Scharf

Dedication

To

My best friend, wife, and eternal companion, Kaylin Bean

Acknowledgements

I am not a “natural” at school work; I remember my angel mother shouting for joy after I narrowly passed Mrs. Wright’s fourth grade class. My father, less of an angel, promised my three sisters and me steak dinners at Jak’s (a nice local restaurant) if we could earn straight A’s in high school, needless to say my sisters know Jak well while I have yet to meet him or see the inside of his restaurant. It is only through my Heavenly Father and the concourses of people around me that I have been able to achieve this endeavor.

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Chapter 1: Literature Review

1.1 Abstract

Corn production across the U.S. Corn belt can be often limited by the loss of nitrogen (N) due to leaching, volatilization and denitrification. The use of canopy sensors for making in-season N fertilizer applications has been proven effective in matching plant N requirements with periods of rapid N uptake (V7-V11), reducing the amount of N lost to these processes. However, N recommendation algorithms used in conjunction with canopy sensor measurements have not proven accurate in many fields of the U.S Corn belt, resulting in inadequate N recommendations. Several soil and weather properties such as soil texture, soil organic matter, total precipitation, and the evenness of precipitation have been observed to effect the interaction between N and corn yield. These interactions influence in-season N fertilizer recommendations. Objectives for this research were 1) to evaluate the performance of published canopy reflectance sensing algorithms used for making in-season corn N fertilizer recommendations and 2) to determine if soil and weather information could be used to make canopy reflectance sensing algorithms more accurate. The application of the second objective was applied with a canopy sensor algorithm developed at the University of Missouri.

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1.2 Introduction

Nitrogen (N) is a plant essential nutrient and the fourth most abundant element in plants after oxygen, hydrogen, and carbon (Zeiger, 2010). Nitrogen is required for the construction and formation of critical plant processes and constituents, such as amino acids, proteins, nucleic acids, coenzymes, hormones, and chlorophyll. For cereal crop production, N is particularly important for obtaining optimal grain yield. This is especially true for supporting corn (*Zea mays* L.) production where it has been found to be most limited by the lack of N (Xie et al., 2013).

Producers often apply uniform amounts of N fertilizer over entire corn fields, usually before or at planting (Cassman et al., 2002). The spatial variability throughout any given field makes it difficult for uniform applications of N fertilizer to meet the needs of every area in the field. The amount of N available in the soil at any particular location within a field is mainly determined by temperature, organic matter, and soil water content (Stanford and Smith, 1971), adding to the complexity of measuring the N supplying power of the soil and making N fertilizer recommendations that are site-specific. The amount of N applied in one part of the field could be adequate for some plants while being inadequate for others. Many studies have been conducted demonstrating that N need is highly variable within fields and justifies variable in-field N fertilizer applications (Mamo et al., 2003; Scharf et al., 2005; Shahandeh et al., 2005; Lambert et al., 2006). When uniformly applied, some field areas will have over-applied N and will result in excessive amounts of N fertilizer; the over-applied N leaches through

the soil and pollutes the surface and ground water. In general, an estimated 50 to 70% of all N applied to the soil is lost (Hodge et al. 2000). Contrary to applying too much N, yield and profit loss occurs in areas that do not receive enough N. In recent decades efforts have been made to reduce the amount of N lost during corn production by improving N use efficiency (NUE).

Working to improve NUE helps ensure the N fertilizer applied is used by the plant and not lost to leaching, volatilization, denitrification, or surface runoff into streams and rivers. One of the best ways to accomplish this is by synchronizing the N fertilizer application or availability with the corn plant's ability to utilize it (Scharf and Lory, 2006). Research has found that the period of rapid N uptake for corn is between the vegetative growth stages of V9 and V18.

In an attempt to accomplish synchrony, active-light crop canopy sensors have been developed and are currently being used by producers to help assist in N fertilizer applications. Initially, these sensors were developed to aid in weed detection (Thorp and Tian 2004). Canopy sensors are commonly used for variable-rate in-season N recommendations in wheat (*Triticum aestivum* L.), cotton (*Gossypium hirsutum* L.) and corn, while experiments and utilization with other crops are also developing (Oklahoma State University, 2016). Resulting success with this technology has led to canopy sensors becoming more and more accepted as an approach to plan and manage N applications. However, due to the soil variability among and within fields, coupled with unpredictable weather, tremendous uncertainty still exists for how to convert reflectance information

into the decision of how much and when to apply N fertilizer to reach optimal yield while not over-applying.

1.3 Canopy Sensors

For decades reflectance sensing of crops has been evaluated for assisting in making management decisions. Soil, crop, and weed light reflectance is unique making it possible to distinguish them from each other. Nitrogen-deprived corn has a specific response to reflectance measurements with increased visible (VIS) reflectance and decreased near-infrared light (NIR) reflectance (Walburg et al. 1982). Due to the absorbance uniqueness between plant species, canopy reflectance data was successfully used as a means of weed detection (Menges et al., 1985).

Canopy sensors gather reflectance data and have been proven to be useful in cereal grain cropping systems. Wheat research has demonstrated how in-season N fertilizer applications, based on sensor measurements, could increase NUE by more than 15% compared to traditional application methods (Raun et al. 2002). In corn production, fifty-five on-farm demonstrations in Missouri found that producer chosen N rates do not perform as well as sensor chosen N rates. Throughout the five year study, a 25% decrease in N was used when compared to the amount of N used by producers. This resulted in an average profit of \$42 ha^{-1} created by not adding N to N-sufficient areas and by adding N to N-deficient areas (Scharf et al. 2011).

While there are several canopy sensors available, perhaps the two most common sensors used have been the GreenSeeker manufactured by Trimble (Trimble

Navigation, Ltd., Sunnyvale, California) and the CropCircle manufactured by Holland Scientific (Holland Scientific, Inc. Lincoln, NE) and marketed by Ag Leader Technology (Ag Leader Technology, Ames, IA) as the OptRx, each having several updates or variations since their original inception. Each sensor has advantages along with disadvantages that will be discussed later.

1.4 How Canopy Sensors Work

Most crop canopy sensors today are considered "active" sensors, meaning they emit their own light source onto the crop canopy making them minimally affected by time of day or cloud cover (Kitchen et al., 2010). Different wavelengths of light from the electromagnetic spectrum are produced simultaneously, typically with selected bands from the VIS and NIR wavelengths represented with light-emitting diodes (Kitchen et al., 2010). Reflectance of the VIS, usually red, is an indicator of the plants photosynthetic health, while NIR is an indicator of the plants structure and ability to assimilate carbon (Kitchen et al., 2010). Different sensor manufacturers use similar wavelengths in an effort to measure the crop's needs. Trimble's GS-506 canopy sensor uses two different wavelengths of light, 650nm and 774nm (VIS and NIR). Holland Scientific's handheld RapidSCAN (CS-45) canopy sensor uses three different wavelengths: VIS, red edge (RE), and NIR, which are 670nm, 730nm, and 780nm, respectively. Green (560nm) and red edge (710nm) wavelengths have, in some instances, been found to be the most sensitive to plant N stress (Scharf and Lory 2009).

Emitted light from the sensor is absorbed by the plant, but not all. Some of the active light is reflected back off the leaf and soil surface, thus active canopy sensors use silicon photodiodes to measure modulated light reflected back from the plant canopy. Reflectance measurements of VIS and NIR are then typically used in some type of ratio calculation. These ratios are referred to as vegetative indices (VI), with the Normalized Difference Vegetative Index (NDVI) the most common among agricultural research. The NDVI and other often used VI are defined in Table 1.1.

The index used for Missouri corn N recommendations employs the inverse simple ratio (ISR; Scharf et al., 2011). The ISR is directly related to the NDVI (Kitchen et al., 2010) as seen below:

$$\mathrm{ISR} = \frac{(1 - \mathrm{NDVI})}{(1 + \mathrm{NDVI})} \qquad [1]$$

Inverse simple ratio values that are closer to zero suggest larger and/or healthier corn while higher values indicate smaller and/or deficient corn. Values above 0.40 are often considered soil readings and are commonly discarded (Kitchen et al., 2010). Inverse Simple Ratio values related to corn N status differences have been found to be comparable to those obtained with the Chlorophyll Index (CI; Solari et al. 2008). Canopy sensor readings are sensitive to growth stage, plant genetics, and other environmental variables.

Nitrogen recommendations are calculated by using reflectance readings from both adequately N fertilized plants as well as those being sensed for fertilization.

Typically, a section of the field that is not N limited, referred to as an N reference or N rich strip, is used to calibrate the sensor to an expected value for a specific growth stage or plant variety when the N supply is sufficient. In order to obtain a N fertilizer recommendation, the VI (such as those shown in Table 1.1) is typically compared to the same index of the sufficiently N fertilized crop. This is often expressed either as a sufficiency (SI) or response index (RI); the SI is more clearly defined as:

$$\mathrm{SI}_{NDVI} = \frac{\text{NDVI N limited crop}}{\text{NDVI non N limited strip}} \quad [2]$$

$$SI_{ISR} = \frac{ISR\ non\ N\ limited\ crop}{ISR\ N\ limited\ crop} \quad [3]$$

The SI_{NDVI} values are expressed from zero to one, with values = 1 representing a crop under no N stress and with values < 1 representing a crop that is N deficient. The SI_{ISR} values are also expressed from zero to one. However, values closer to zero represent a crop under no N stress and values farther from zero represent a crop that is N deficient. Occasionally, some will invert the SI to create a response index (RI), where values > 1 represent a crop with greater responsiveness to N fertilizer.

1.5 Limitations of Canopy Sensors

While canopy sensors have contributed to better in-season N fertilizer applications and have helped increase NUE (Randall et al., 2003; Roberts et al., 2012), they still suffer from limitations. Moisture on leaves can disrupt the integrity of the reflected light depending on the type of wavelengths used in the specific sensor (Schepers, 2008). Green and amber wavelengths are affected the most, up to 8%,

resulting in highly skewed red reflectance values (Schepers, 2008). This makes it difficult to know if the canopy sensor has collected all of the reflected light from the plant tissue.

It has been found that vertical light penetration in the canopy is sensor dependent. The GS-506 was proven to penetrate deeper into the canopy while the CC-210 was less successful at infiltrating the canopy (Barker and Sawyer, 2013). The GS-506 measurements changed as the lower leaves in the canopy were removed suggesting that the light emitted by the sensor was reaching the lower canopy. However, the CC-210 measurements did not change as the lower leaves in the canopy were removed (Barker and Sawyer, 2013).

Research also suggests that not all active canopy sensors work equally as well during the day and night as manufacturers claim (Barker and Sawyer, 2013). Results showed that the GS-506 measured differences in both NIR and VIS reflectance values during diverse lighting conditions throughout the day (caused by time of day, cloud cover, etc.) and night. Less light reflectance was measured during the night compared to the measurements taken during the day. This suggests that a greater VI value, such as NDVI, would be calculated when the sensor is used in times of limited light resulting in a lesser N fertilizer recommendation. However, these various lighting conditions did not affect the CC-210's measurements in either the VIS or NIR wavelengths, supporting the manufacturer's claims.

Calibration is also sensor dependent; some sensors, including the GS-506, need to be recalibrated to the N reference strip quite frequently while others do not. When

calibrating the sensors, it is crucial to make sure the N reference strip uses the same hybrid and is in the same growth stage as the N-deficient corn.

1.6 Algorithms Developed for N Fertilizer Recommendations

No standard algorithm exists for making corn N fertilizer recommendations. Thus, it is difficult to know which algorithm should be used or which is most accurate for a specific area or situation. Various institutions, universities, and businesses have created algorithms in order to convert the reflectance values, collected by the canopy sensor, into an N fertilizer recommendation. As would be expected, the general trend of these algorithms shows an increase of N fertilizer recommendations with a lower SI or an increase in RI, but uniqueness exists.

Select algorithms (i.e. University of Nebraska) were initially modeled after an algorithm developed for N fertilizer recommendations using chlorophyll meters (Solari et al., 2010). In an effort to generalize an algorithm that could be used with both chlorophyll meters and active sensors alike, Holland and Schepers (2010) crafted an algorithm using the corn plant's N response curve and general production information gathered by the user or producer. This allowed for any VI to be used when calculating the SI. Other algorithms (i.e. Oklahoma State University) consider a "mass balance" approach, accounting for already available N, referred to as N credits, and some level of expected NUE. Table 1.2 lists the different information collected and used by several institutions to calculate their respective N fertilizer recommendation. Variables

calculated from the information gathered are then used to determine site specific N fertilizer recommendations (see Table 1.3).

1.7 The Role of Soil and Weather on Corn Nitrogen Response

Nitrogen fertilizer recommendations based on the interactions of soil and weather conditions are extremely limited (Tremblay, 2004). Weather largely determines the biological activity in soil; which includes the decomposition of soil organic matter (Bolinder et al., 2007; van Es et al., 2007; Lokupitiya et al., 2010). Soil mineral N has been found to be affected by both precipitation and thermal units, which in turn ultimately affect corn's response to N (Tremblay, 2004; Tremblay and Belec, 2006; Shanahan et al., 2008; Kyveryga et al., 2007). In some soils such as a Brookston clay soil (a fine-loamy, mixed, superactive, mesic Typic Argiaquoll), 80% of the variability seen in corn yields is a result of temperature and precipitation (Dirks and Bolton, 1981). As such, NUE is also largely affected by precipitation and temperature. A greater response to N fertilizer is generally seen during wet years than during dry years (Yamoah et al., 1998). Nitrogen response to added N across North America was found to be most affected by the precipitation during June and July as well as temperatures during July and August (Jeutong et al., 2000). Some have suggested that the distribution of rainfall is as equally important and should be considered when managing N (Shaw, 1964; Reeves et al., 1993). For example, total rainfall for any given month of 15 cm spread out over six events over the month will have a vastly better impact on the soil and crop than one rainfall event totaling 15 cm. The Shannon Diversity Index (SDI) is one of many indices that has been used to quantify rainfall distribution. A SDI value of one would suggest a

complete evenness of rainfall over a given period of time while a value of zero would suggest a complete unevenness of rainfall.

In more arid climates, it was found that soils containing more clay return greater yields (Tremblay et al., 2011). However, in wet climates soils with a coarser texture result in greater yields. Therefore, a 51 site-year meta-analysis was performed by Tremblay et al. (2012) to determine N response of corn when compared to soil texture, total precipitation (PPT), corn heat units (CHU), SDI, and abundant and well-distributed rainfall (AWDR). Table 1.4 shows the equations needed to calculate PPT, CHU, SDI and AWDR (Tremblay et al., 2012).Research concluded soil texture was, to a large degree, the most influential factor in determining corn response to N. The average response to N fertilizer over the entire 51 sites for fine textured soils was greater than the average response for medium textured soils. Alone, CHU values were only able to explain a small variation in N fertilizer response. In addition to soil texture, PPT, SDI, and AWDR were significant in influencing the corn's response to N fertilizer.

1.8 Merging Soil and Weather Information with Canopy Sensing

Nitrogen is a "reactive" element sensitive to both soil and weather conditions, making it difficult to know how much soil N is available to the crop at any one specific moment. Soil texture, PPT, and distribution, as well as their interaction, have an important impact on corn's response to N fertilizer (Tremblay et al., 2012). Clayey soils can have a positive and negative effect on yield, based on the PPT throughout the growing season (Shahandeh et al., 2011). Presently, canopy-sensing algorithms are not

adjusted to include soil and weather information. Doing so could improve the accuracy of the sensors in making more robust N fertilizer recommendations. Others have demonstrated site-specific soil information that could improve canopy-sensing predictions of crop N need (Roberts et al., 2012, Kitchen et al., 2010). Soil properties could be used to distinguish different soil management zones while also acknowledging that canopy sensor algorithms need adjustment accordingly (Roberts et al., 2012). Most soil information available, such as the USDA SSURGO database, only broadly specifies texture, chemical, and physical soil properties. This information may or may not aid in making N recommendations.

Given this background, there are three needs that I proposed with this thesis research. The first is to better understand, in a side-by-side fashion, how different algorithms perform in corn N fertilizer recommendations given the same crop canopy sensing information. Second, explore the possibility of predicting optimal N rates only using soil and weather data. And third, assess if canopy sensor N rate algorithm performance can be improved when modified with soil and weather information.

1.9 Objectives

The purpose of this research is to:

1. Evaluate the performance of published canopy reflectance-sensing algorithms for making in-season corn N fertilizer recommendations.
2. Determine if soil and weather information can be used to predict optimal N fertilizer rates.

3. Assess if canopy sensor N recommendation algorithms modified with soil and weather information out perform uninformed canopy sensor N recommendation algorithms.

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1.11 Tables and Figures

Table 1.1. A list of various vegetative indices used in conjunction with reflectance sensing.

Vegetative Index	Equation
Normalized difference vegetative index (NDVI)	NIR – Red/NIR + Red
Normalized difference red edge (NDRE)	NIR – Red Edge/NIR + Red Edge
Amber normalized difference vegetative index (ANDVI)	NIR – Amber/NIR + Amber
Green normalized difference vegetative index (GNDVI)	NIR – Green/NIR + Green
Chlorophyll index (CI)	$(R_{NIR}/R_{Green}) – 1$
Simple Ratio (SR)	NIR/VIS
Inverse Simple Ratio (ISR)	VIS/NIR

Table 1.2. Information needed by three select algorithms to produce an in-season N fertilizer rate recommendation.

	Information Collected											
Institution or Business	Planting Date	Sensing Date	N – Rich VI	Target VI	Expected NUE	N fert. price	Corn grain price	Pre-plant N rate	% N in grain	Max yield	N opt or EONR	ResidualN
University of Missouri	-	-	X	X	-	-	-	-	-	-	-	-
Oklahoma State University	X	X	X	X	X	X	X	X	X	X	X	-
Holland Scientific	-	X	X	X	-	X	X	X	-	X	X	X

Table 1.3. Four canopy sensor algorithms and input variable descriptions for each.

University/Institution	Algorithm	Algorithm Variable Description
University of Missouri	N_{app} =(280 kg N ha^{-1} x $ratio_{target}/ratio_{reference}$) – 224 kg N ha^{-1}	$ISR_{N\text{-}limited} = VIS_{N\text{-}limited}/NIR_{N\text{-}limited}$ $ISR_{non\ N\text{-}limited} = VIS_{non\ N\text{-}limited}/NIR_{non\ N\text{-}limited}$
Holland Scientific	$N_{app} = (MZ_i \times N_{OPT} - N_{PreFert} - N_{CRD} + N_{COMP}) \times \sqrt{(1 - SI)}/DeltaSI$	$SI = VI_{non\ N\text{-}limited}/VI_{N\text{-}limited}$ DeltaSI = Difference between where SI = 1 and where the N response curve intersects the y-axis N_{CRD} = Credits from the previous crop (manure applications, residual nitrogen from legumes, etc.) $N_{PreFert}$ = The total amount of fertilizer applied before sensing or topdress N_{OPT} = Maximum rate prescribed by producers or the EONR N_{COMP} = N required by the crop in addition to N_{OPT} due to soil limitations or growth stage
University of Nebraska (original)	$N_{app} = 317\sqrt{0.97 - SI}$	$SI = VI_{non\ N\text{-}limited}/VI_{N\text{-}limited}$ 0.97 = The point at which addition N response is not expected.
Oklahoma State University	$N_{app} = ((YP_O - YP_N) \times 56 \times \%N\ in\ grain/100)/NUE$	$YP_o = 2592^{(NDVI/Sum\ of\ GDD*1775.6)}$ NDVI = NIR – Red/NIR + Red $GDD = (T_{MAX} + T_{MIN}/2) - 50$ $YP_N = YP_O \times RI$ RI = avg NDVI of N rich / avg NDVI of farmer practice %N in grain = constant value based on regional research NUE = constant value chosen to be a likely NUE

Table 1.4. Equations used to calculate each weather variable.

Weather Variable	Equation
Sum of the total rainfall (PPT)	Sum of the daily rainfall.
Corn heat units (CHU)	$\sum(Y_{max} + Y_{min})/2$; Y_{max} and Y_{min} are the daily maximum and minimum temperatures.
Shannon diversity index (SDI)	$[-\sum pi \ln(pi)]/\ln(n)$; pi = Rain/PPT (daily rainfall relative to total rainfall in a given time; n = number of days.
Abundant and well-distributed rainfall (AWDR)	PPT X SDI

Chapter 2: Evaluating Three Publically Available Canopy Sensor Algorithms

2.1 Abstract

Corn production across the U.S. Corn belt can be often limited by the loss of nitrogen (N) due to leaching, volatilization and denitrification. The use of canopy sensors for making in-season N fertilizer applications has been proven effective in matching plant N requirements with periods of rapid N uptake (V7-V11), reducing the amount of N lost to these processes. However, N recommendation algorithms used in conjunction with canopy sensor measurements have not proven accurate in many fields of the U.S. Corn belt, resulting in poor N recommendations. Objectives for this research were to evaluate the performance of published canopy reflectance sensing algorithms used for making in-season corn N fertilizer recommendations. Nitrogen response trials were conducted across eight states and two growing seasons, totaling 32 sites (four per state) with soils ranging in productivity. Reflectance measurements at ±V9 were used with three different canopy sensor algorithms to calculate an in-season N rate fertilizer recommendation. These recommendations were related to the economic optimal N rate (EONR). Algorithms developed by the University of Missouri, Oklahoma State University, and Holland Scientific were only mediocre in predicting EONR. Across growing seasons, algorithm suggested N fertilizer recommendations were within 61 to 113 kg N ha^{-1} of EONR when target corn received no N at-planting and within 74 to 118 kg N ha^{-1} when target corn received 45 kg of N/ha at-planting.

2.2 Introduction

Efficient nitrogen (N) management in corn (*Zea mays* L.) is critical for increasing grower profits and preventing environmental pollution. Fertilizer applications that match end-of-season measured economic optimum N fertilizer rate (EONR) can reduce N loss while protecting grower profits and the environment (Scharf et al., 2002; Roberts et al., 2010; Scharf et al., 2011). However, within-field spatial variability of soil characteristics and variation in year-to-year weather factors make it difficult to determine the correct amount of N fertilizer needed early in the season to match EONR.

Crop canopy reflectance sensors capture plant condition information in small areas within fields and therefore can assess spatially-variable N requirements. Such a diagnostic tool could aid in recommending the correct amount of N fertilizer applied to reach optimal yields (Scharf et al., 2002; Kitchen et al., 2010; Barker and Sawyer, 2010; Scharf et al., 2011). Unlike soil- or tissue-test based in-season N fertilizer rate recommendations, canopy sensors are directly mounted to a fertilizer applicator making it possible to collect reflectance data and apply variable N fertilizer rates in an on-the-go operation. Additionally, gathering reflectance data isn't limited by time of day or cloud cover.

Canopy sensors emit visible and near infrared wavelengths of modulated light onto the corn canopy and measure the amount reflected back (Shanahan et al., 2003). The photosynthetic health of a corn plant can be determined by using the relative absorption of visible wavelengths of light, while the plant's structural size is primarily captured using near infrared wavelengths. Typically both types of wavelengths are

measured by canopy sensors and some type of vegetative index is calculated (Kitchen et al., 2010). The index is directly related to the N health of the plant. Compared to chlorotic and deficient N plants, healthy green corn plants absorb more visible light, and as the plant gets larger in size the reflection of near infrared light increases. Thus, the application of reflectance canopy sensing for N management often is based upon the relative reflectance readings between adequately N fertilized corn and N deficient corn (Biggs et al., 2002; Kitchen et al., 2010). Reflectance data are first gathered from a strip or area in the field that is not N-limited. This is called an N reference or N rich strip and is usually established at planting by applying sufficient amounts of N fertilizer. An alternate approach to an N reference is a virtual N reference strip, where no extra N fertilizer is applied. In this approach a distribution of reflectance measurements is obtained from several passes through the field and an average value is calculated from the healthiest looking corn (Holland and Schepers, 2013). The virtual N reference value can be updated as the sensing applicator progresses through other parts of the field. Following the N reference strip or virtual N reference, reflectance data are then obtained from corn plants intended for fertilization (sometimes referred to as the 'target' corn). Using an N reference strip normalizes the reflectance data and sets a standard for defining the deficiency of 'target' corn. Depending on field size and variability, multiple N reference strips may be required to capture major soil or landscape differences (Sheridan et al., 2012). Gathered reflectance data are then used with an algorithm to produce an N fertilizer recommendation. These algorithms are

considered to be at the core of successful canopy sensor based N fertilizer management (P.C. Scharf, 2010) and will be discussed in further detail later.

Financial benefits have been documented by using canopy sensors to synchronize the application of N fertilizer with corn N uptake. Fifty-five on-farm trials during 2004 to 2008 were conducted in Missouri where canopy sensing was used to inform topdress N fertilizer application (Scharf et al., 2011). Sensing N rates were then compared to a fixed rate that producers' used on these same fields. Across all fields, canopy sensors increased partial grower profits by an average of \$42 ha^{-1} over producer rates. In another assessment over three differing soil areas conducted from 2004 to 2007 canopy sensor N fertilizer applications performed better than producer chosen N fertilizer applications on about half of 16 field-scale experiments (Kitchen et al., 2010). On average they found using canopy sensing generated a \$25 to \$50 ha^{-1} profit.

Canopy reflectance sensing for corn N management does have its limitations. Nitrogen stress must be detectable by the sensors when reflectance readings between the N reference strip and target plots are compared (Barker and Sawyer, 2010; Solie et al., 2012; Franzen et al., in-review, 2016). If no difference between them exists, there is no basis for N application. Since plant N uptake is minimal early in the growing season and N stress does not typically show until after the V6 growth stage, producers are forced to wait (Barker and Sawyer, 2010). If producers wait too late they run the risk of corn plants too tall for the equipment they have available for fertilization. More recently specialized high-clearance equipment has become more available for these types of applications. Extended wet periods may also prohibit timely field operations, reducing

the time available for sensor-based N fertilizer applications. Select models of canopy sensors, while claiming to be unaffected by cloud cover or time of day, has proven opposite (Barker and Sawyer, 2013). Furthermore, establishing N reference strips requires extra time to apply sufficient N fertilizer and can be cumbersome.

Canopy sensor algorithms are the mathematical expressions used to transform reflectance readings into an in-season N recommendation. The unique growing conditions and environments these algorithms were developed for may limit their universal adoption. Also, most algorithms are dependent upon the make and model of the canopy sensor used to create it, making it difficult to use one algorithm with multiple canopy sensors. These circumstances create challenges when determining which algorithm or canopy sensor will work best and under what conditions. Utilizing different approaches for corn, many canopy sensor algorithms have been developed. Three widely used algorithms are from the University of Missouri (Scharf et al., 2011), Holland Scientific (Holland and Schepers, 2010), and Oklahoma State University (Oklahoma State University, 2016). The University of Missouri corn algorithm is a linear-based model requiring only the gathered canopy reflectance measurements. Variations have been made to accommodate early-, mid-, and late vegetative growth stages. The Holland Scientific algorithm examined in this study is a quadratic-based model that includes several user and producer inputs along with the canopy reflectance data. The Oklahoma State University corn algorithm uses a number of input variables, such as N use efficiency, growing degree days (GDD), grain protein content, and an expected yield, to determine the N fertilizer rate.

Research is needed to determine how well these algorithms perform across a large regional area, such as the U.S. Corn Belt. Such performance comparison could lead to the information needed to develop more robust algorithms for making in-season N fertilizer recommendations. The objective of this chapter is to evaluate the performance of the University of Missouri, Holland Scientific, and Oklahoma State University crop canopy reflectance algorithms used for making in-season corn N recommendations. A sub-objective is to compare the effect of corn receiving no N fertilizer at planting with corn fertilized with a modest amount at planting on the reflectance algorithm recommendations.

2.3 Materials and Methods

2.3.1 Research Sites and Locations

This research was conducted as part of public-private collaboration between eight major land-grant universities (University of Iowa, University of Illinois, University of Indiana, University of Minnesota, University of Missouri, North Dakota State University, University of Nebraska, and the University of Wisconsin) within the U.S. Corn Belt and DuPont Pioneer. This project is commonly referred to as the, “Performance and Refinement of Nitrogen Fertilization Tools” project. The approach for this research was fundamental N fertilizer application response field-plot studies conducted with standardized protocols and methods across a wide range of soil and weather conditions. Yield and soil measurements from these plot studies provided both the measurements

needed to generate N recommendations with the sensing algorithms as well as N response functions.

Thirty-two corn N response trials were conducted during 2014 to 2015 in eight Midwestern Corn Belt States. In each state, two sites ranging in productivity were selected for each growing seasons, giving four sites per state (Figure 2.1). Productivity was determined by historical yield and general soil productivity. Research sites were planted at a target population of 86,450 plants ha^{-1} using Pioneer hybrids (DuPont Pioneer, Johnstown, IA) found suitable for the selected sites within the region. Most research sites followed soybean, however four sites followed corn. The MN New site and the IA Mason site were tiled. Both NE sites were irrigated and all but three sites received at least some form of tillage. Planting dates ranged from April 19 – May 23 and canopy sensor dates ranged from June 7 – June 27. Descriptions of management for all sites are presented in Tables 2.1 and 2.2.

2.3.2 Plots and Treatments

Plot dimensions were state and site dependent and were determined by the planting (planter width) and harvesting (combine width) equipment available, but minimal plot harvest area was 18.6 m^2. Average size per site was 0.4 ha. Sixteen different N application treatments, replicated four times (totaling 64 plots per site), were used in a randomized complete block design (Table 2.3). Nitrogen treatments were obtained using dry-prilled NH_4NO_3 fertilizer broadcast applied. The “at-planting” fertilizer was applied within 48 hours of initial planting while the topdress fertilizer was applied between the V8 to V10 leaf stage immediately following canopy sensing.

Treatment one was the non-fertilized control. Treatments 2 to 8 received all N at-planting in 45 kg N ha^{-1} increments from 45 to 315 kg N ha^{-1}, while treatments 9 to 14 received 45 kg N ha^{-1} at-planting and the rest at topdress in 45 kg N ha^{-1} increments from 45 to 270 kg N ha^{-1}. Treatments 15 and 16 received 90 kg N ha^{-1} at-planting with the remaining N at topdress.

2.3.3 Canopy Sensing

Reflectance measurements were collected using the RapidSCAN CS-45 (RS) Handheld Crop Sensor (Holland Scientific, Lincoln, NE) just prior to topdress application (growth stage V8-V10 leaf stage). Manufacturer recommendations were followed during initial canopy sensor setup. The sensor was held approximately 60 cm above the row as the operator steadily walked approximately 4 kph alongside the row. Only plot rows used for yield measurements were sensed. While the RS uses three different wavelengths of light, red (670 nm, VIS), red edge (720 nm, RE), and near-infrared (780 nm, NIR), only VIS and NIR were utilized in calculating vegetative indices for the N rate algorithms tested in this study.

2.3.4 Algorithms

Three algorithms for making corn N fertilizer recommendations were chosen for performance comparison.

2.3.5 University of Missouri (MU)

The MU algorithm tested here was an equation developed for the V8-V10 growth stage (Scharf et al., 2011). The vegetative index used in this algorithm is the Inverse Simple Ratio (ISR) and is defined as:

$$ISR = \frac{VIS}{NIR} \qquad [1]$$

Where VIS = reflectance of the visible wavelength, and NIR= reflectance of the near infrared wavelength. Measurements are taken to obtain ISR values from both N reference corn ($ISR_{reference}$) and target corn (ISR_{target}). The N recommendation is then calculated as follows:

$$NRec_{MU} = \left(280\ kg\ N\ ha^{-1} \times \frac{ISR_{target}}{ISR_{reference}}\right) - 224\ kg\ ha^{-1} \qquad [2]$$

where $NRec_{MU}$= the recommendation in kg ha^{-1}.

One complication was this recommendation algorithm was developed with the Holland Scientific's Crop Circle 210 (CC-210), an earlier sensor model than the RS used in this study. Thus in order to test this algorithm, reflectance measurements gathered with the RS had to be converted to equivalent CC-210 measurements. Simultaneous measurements from these two sensors were taken on V8-V10 corn stands over several growing seasons (unpublished data) and found related in the following way:

$$ISR = 0.454 + \ln(ISR_{RS}) \times 0.125 \qquad [3]$$

where ISR= Inverse Simple Ratio needed for the MU algorithm, and ISR_{RS} = Inverse Simple Ratio of the RS. Once RS values were transformed into equivalent CC-210 values, the recommendation could be determined using Eq.[2].

2.3.6 Holland Scientific (HS)

The HS equation (Holland and Schepers, 2010) for corn N fertilization is not specific to any one vegetative index. In this analysis the normalized difference vegetative index (NDVI) was used and is calculated as:

$$NDVI = \frac{(NIR-VIS)}{(NIR+VIS)} \quad [4]$$

where NIR = the amount of NIR reflectance and VIS = the amount of VIS reflectance.

$$SI = \frac{NDVI_{target}}{NDVI_{reference}} \quad [5]$$

The final N fertilizer recommendation is calculated as follows:

$$NRec_{HS} = (MZ_i \times (N_{OPT} - \sum N_{CRD} + N_{COMP})) \times \sqrt{(\frac{1-SI}{\Delta SI})} \quad [6]$$

where $NRec_{HS}$ = the N fertilizer recommendation in kg N ha^{-1}. MZ_i = management or soil sample scalar/adjustment; N_{OPT} = maximum amount of N fertilizer applied by the producer or anticipated EONR; N_{CRD} = N credits including pre-plant or topdress fertilizer applied before sensing, manure N, nitrate found in the soil water or previous leguminous crops, all in kg N ha^{-1}; N_{COMP} = amount in excess of N_{OPT} needed to satisfy soil limited conditions (kg N ha^{-1}). The information needed to calculate N_{OPT} and

N_{CRD} was obtained for all sites from the research station's or producer's site history records. The ΔSI = the difference between where SI is equal to one and the point at which the response curve intersects the y-axis. For this assessment MZ_i was =1 and the N_{COMP} adjustment was excluded.

2.3.7 Oklahoma State University (OSU)

This equation was originally developed using the NDVI (Oklahoma State University, 2016) and is calculated by first computing the following:

$$RI = \left(\frac{NDVI_{reference}}{NDVI_{target}}\right) \times 1.64 - 0.53 \quad [7]$$

$$INSEY = \frac{NDVI}{Cummulative\ GDD} \quad [8]$$

$$YP_O = 2592^{(INSEY \times 1775.6)} \quad [9]$$

$$YP_N = YP_O \times RI \quad [10]$$

$$GDD = \frac{T_{Max} + T_{Min}}{2} - T_{Base} \quad [11]$$

where INSEY = an in-season estimated yield, YP_O = the yield potential without N added, and YP_N = the yield potential with N added. The T_{Max} = the maximum temperature, T_{Min} = the minimum temperature and T_{Base} = 10° C. Temperature needed to calculate growing degree days (GDD) was collected using a HOBO Link mobile weather station instrumented at each site. The N recommendation was then calculated by:

$$NRec_{OSU} = \frac{(YP_N - YP_O) \times \%N\ in\ grain}{expected\ NUE} \quad [12]$$

where $NRec_{OSU}$ = the N fertilizer recommendation in kg N ha^{-1}. A NUE value of 0.5 and a %N in grain value of 0.0125 were used across all sites.

This recommendation algorithm was developed using the GreenSeeker (GS-506) canopy reflectance sensor manufactured by Trimble (Trimble Navigation, Ltd., Sunnyvale, California), a completely different make and model from the RS. Thus, transformations of reflectance data were also needed. The CC-210 and GS-506 were simultaneously used to take reflectance measurements on corn stands throughout several growing seasons (unpublished) and were found related in the following way:

$$GS\_506_N = 1.24 \times CC\_210_N - 0.0903 \quad [13]$$

Where GS_506_N = GS-506 reflectance values and CC_210_N = reflectance gathered by the RS that was transformed to be CC_210 equivalent using Eq. 3. This algorithm used the NDVI making the final step the conversion between ISR and NDVI.

$$NDVI = \frac{(1 - ISR)}{(1 + ISR)} \quad [14]$$

Following these transformations, the recommendation could be calculated using Eq. [12].

2.3.8 Reflectance Measurements for Recommendations

Nitrogen application treatments used to calculate an average site level N-rich reference were those that received 135, 180, and 225 kg N ha^{-1} at-planting (Treatments 4, 5, and 6 in Table 2.3; n=12). The exception was the Lonetree site where because of

extreme early-season N loss, noted with a visual N deficiency the plots that received 315 kg N ha^{-1} at-planting were used as the N-rich reference. Nitrogen recommendations were calculated using two scenarios to represent the target corn to be fertilized at ~V9. One was the average of all experimental units fertilized at planting with 45 kg N ha^{-1} (n=28), and the other from unfertilized experimental units (0 kg N ha^{-1}; n=4). Canopy sensor reflectance data from both the target plots and N reference plots were used to calculate the vegetative indices specific to all three algorithms. The ISR was calculated for the MU algorithm and the NDVI was calculated for both the HS and OSU algorithms. It should be mentioned that the HS algorithm is not limited to just the NDVI, other VI such as the NDRE index could have been used.

2.3.9 Performance Evaluation and Statistics

Data were analyzed by site using SAS version 9.2 (SAS Institute Inc., Cary, NC). For calculating EONR, a quadratic-plateau function was used since it has generally been found to be the best model in describing corn yield response to N (Scharf et al., 2005; Cerrato and Blackmer, 1990). Proc NLIN in SAS 9.2 was used to fit the data to the quadratic-plateau function. The EONR was calculated for all 32 site years using treatments 1, 2 and 9-14 (Table 2.3) as shown:

$$EONR = \frac{(-b-(ratio)}{(2c)} \qquad [15]$$

where *b* and *c* = linear and quadratic response coefficients from optimized quadratic function, and ratio = \$0.88 kg^{-1} N/\$0.03 kg^{-1} grain (i.e., N price/corn price). The EONR was set to not exceed the maximum N rate (315 kg N ha^{-1}).

The performance of each of the algorithms was evaluated by comparing the N recommendation to the site level top-dress EONR that was determined using the total season-long N application. As such, scenarios where the N recommendation used plots fertilized with 45 kg N ha^{-1} at-planting had that amount added to each algorithm N recommendation before the comparison. Algorithm performance was based on the root mean square errors (RMSE) and the median and mean difference between the algorithm N recommendation and EONR. Over all sites, the mean and median of this difference are measures of the algorithm accuracy, and the RMSE of this difference over all sites is a measure of precision.

The RMSE was calculated for each algorithm as follows:

$$RMSE = \sqrt{\frac{\sum(N_{Alg} - N_{EONR})^2}{n}} \qquad [16]$$

where N_{Alg} = the algorithm N rate recommendation, N_{EONR} is the measured EONR, and *n* is the total number of site years.

Box and whisker plots where made using Grapher 11 (Golden Software, Golden, CO) to graphically represent the median, upper and lower quartiles, and the range of each algorithm's difference at both the 0 and 45 kg N ha^{-1} at-planting rates. Median values close to zero suggest accuracy while values well above or below zero suggest inaccurate algorithm N fertilizer rate recommendations.

2.4 Results and Discussion

2.4.1 Algorithm Performance

Algorithm N fertilizer recommendations for 32 sites are shown relative to EONR in Table 2.4 and scatter plots in Figures 2.2 - 2.4. Points on or near the 1:1 diagonal line indicates the algorithm performed well for making an N recommendation. Points below the line represent a recommendation that underestimated N need and sites above the line represent an over-estimated N recommendation. Recommendations were generally greater and better performing when target corn received no N at planting versus corn fertilized with 45 kg N ha^{-1} at planting. This shift would be expected since a crop unfertilized at planting would by the V9 growth stage show more N deficiency, and is evidence of the responsiveness of the sensor and algorithm to reflectance properties of the corn canopy. While this may be true, the likelihood of widespread adoption of applying no N at planting is minimal. Foul weather, imperfect soil conditions, and potential mechanical problems may arise shrinking the time available to apply N fertilizer further increasing the risk of applying all N fertilizer in-season. If no N is applied later in the growing season, substantial yield loss follows. These observations support the suggestion that canopy sensors should be reserved for areas where N stress is considered the most limiting plant growth factor (Barker and Sawyer, 2010; Solie et al., 2012).

Average differences between the algorithm N recommendations and EONR for corn receiving no N at planting are shown in Table 2.5. The same information is graphically represented in Figures 2.5 to 2.7. Generally, all the algorithms

underestimated the EONR fertilizer recommendation while the farmer chosen N rates generally overestimated the EONR fertilizer recommendation. Ranking of algorithm performance and farmer chosen N rates based on the mean difference and RMSE was MU<HS<farmer<OSU. The MU algorithm N fertilizer recommendations were within 30 kg N ha^{-1} for approximately 34% of the sites. The HS algorithm N fertilizer recommendations were within 30 kg N ha^{-1} for 28% of the sites and the OSU algorithm was within 30 kg N ha^{-1} for only 9% of the sites.

Similarly, average differences between the algorithm N recommendations and EONR for corn receiving 45 kg N ha^{-1} at planting are also shown in Table 2.5. The same information is graphically represented in Figures 2.5 to 2.7. To a greater extent, all the algorithms underestimated the N fertilizer recommendations. Ranking of algorithm performance and farmer chose N rates based on the difference mean and RMSE was MU<farmer<HS<OSU. The MU algorithm N fertilizer recommendations were within 30 kg N ha^{-1} for approximately 31% of the sites. The HS algorithm N fertilizer recommendations were within 30 kg N ha^{-1} for 16% of the sites and the OSU algorithm was within 30 kg N ha^{-1} for 9% of the sites.

Other reasons to consider for differences found among algorithm recommendations and EONR might be the unique construction of each algorithm. The MU algorithm is especially sensitive to reflectance values. The greater the difference between the N reference corn reflectance and the target corn reflectance, the more N fertilizer recommended. This was observed here when the two different target corn N rates were used. When N was applied at planting algorithm performance suffered. It

should be noted that those using the MU algorithm are instructed to apply 56 kg N ha^{-1} at planting. If the target corn is not responsive, the MU algorithm simply cannot recommend accurate N fertilizer rates.

The HS algorithm is also somewhat sensitive to changes in reflectance between the N reference and target corn. Perhaps more significant is the effect of N_{COMP} on the final N recommendation. The N_{COMP} variable considers historical, personal, and field-specific information provided by the producer's experience. Several HS algorithm N recommendations could have benefited from the input of this variable. The Lonetree, Troth2, Brown, Urbana, and Brown2 sites are vulnerable to denitrification (personal experience and communication). Knowing this an extra amount of N fertilizer could have been applied to compensate for possible N loss. Likewise, the SCAL and SCAL2 sites are prone to N leaching. An added amount of N fertilizer could have been applied in preparation for possible N loss. The Belmont site is historically non-responsive to added N (personal communication) potentially leading to a smaller N fertilizer recommendation. Including N_{COMP} in this analysis likely would have improved the HS algorithm N fertilizer recommendations.

Following a sensitivity analysis on the OSU algorithm, it was determined that reflectance measurements were not as influential in calculating an in-season N fertilizer recommendation as were the HS and MU algorithms. The amount of GDD had the greatest effect on the final N recommendation. Combined with gathered NDVI values, GDD were used to calculate *INSEY* which were then used to calculate YP_o, which were finally used to calculate the N fertilizer recommendation. It was observed that as GDD

decreased, the final recommendation increased. However, if the GDD were decreased too much, no N was recommended suggesting it was past rescuing. Also, as the GDD increased, the N recommendations decreased. This analysis demonstrates, when using the OSU algorithm, the time of sensing is extremely important. Waiting too long to sense and apply N fertilizer could result in an incorrect recommendation.

2.4.2 Differences among Growing Seasons

The decline in accuracy seen in the MU and HS algorithms for the 2015 growing season may be attributed to unpredictable weather and soil variability. At several sites, precipitation before and following sensing was excessive and frequent (Table 2.6). The 2015 Troth2 site received 28 cm of rain between sensing to plant maturity which is three times as much as the 2014 Troth site. Similarly the 2015 Lonetree site, located on a claypan soil, received twice as much precipitation as the 2014 Bay site, also located on a claypan soil. Excessive precipitation on claypan soil creates an environment for both significant surface runoff (surface saturation) and denitrification (Blevins et al., 1996). Nitrogen loss prior-to-sensing may be captured and corrected by the canopy sensor but post-sensing N loss cannot be corrected. This results in inaccurate N fertilizer recommendations. Also, the N recommendations given by the MU and HS algorithms are highly sensitive to the difference in reflectance readings between the targets and N-reference. Larger differences generally result in closer to EONR N fertilizer recommendations. Interestingly the OSU algorithm performed opposite of the MU and HS algorithms. The OSU algorithm performed better in 2015 than 2014. It is possible

that OSU's incorporation of GDD helped account for the added environmental variability observed in 2015.

Currently the algorithms mentioned above do not account for weather conditions such as total precipitation, intensity and frequency of precipitation, or growing degree days (OSU does incorporate GDD). Others (Tremblay et al., 2012; Xie et al., 2013) have shown that total precipitation, rainfall evenness (as measured with the Shannon Diversity Index), and the product of these two (total precipitation X Shannon Diversity Index and called the "abundant and well-distributed rainfall") are important factors for understanding corn N response. Perhaps the unique growing conditions and environments these algorithms were developed for and the transformation of reflectance data to become sensor equivalent hindered the performance of these algorithms. More research could help address these issues.

Further, the HS algorithm may have performed better if a different vegetative index was used such as the normalized difference red-edge (NDRE) index or if all inputs offered were used in this analysis. Research across 11 site-years and three states found that the HS algorithm, using the NDRE and all available inputs, recommended lesser in-season N fertilizer applications than a crop model (Maize-N) for 9 of the 11 site-years, resulting in higher agronomic efficiency and partial factor productivity of N (Thompson et al., 2015).

2.5 Conclusion

All three algorithms, across both years, performed the best when the no N at planting plots was used as the target corn. When graphically comparing the algorithm recommendations with the corresponding site-level EONR values it is apparent that the MU and HS algorithms generally underestimated EONR while the OSU algorithm almost always underestimated EONR.

The difference in performances between target N rates may be attributed to the ability of the canopy sensor to detect an N deficiency in the corn crop at the time of sensing. If at sensing the target corn does not show any signs of N stress, resulting in a similar greenness and biomass between the target crop and N-reference crop, then the algorithms recommend minimal amounts of N, ultimately underestimating EONR. Differences in algorithm performances between growing seasons are attributed to the amount of precipitation from the time of sensing to the time of plant maturity and the variable make-up of each algorithm. Research is needed to determine if accounting for certain soil and weather properties can improve the accuracy of these algorithms.

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2.7 Tables and Figures

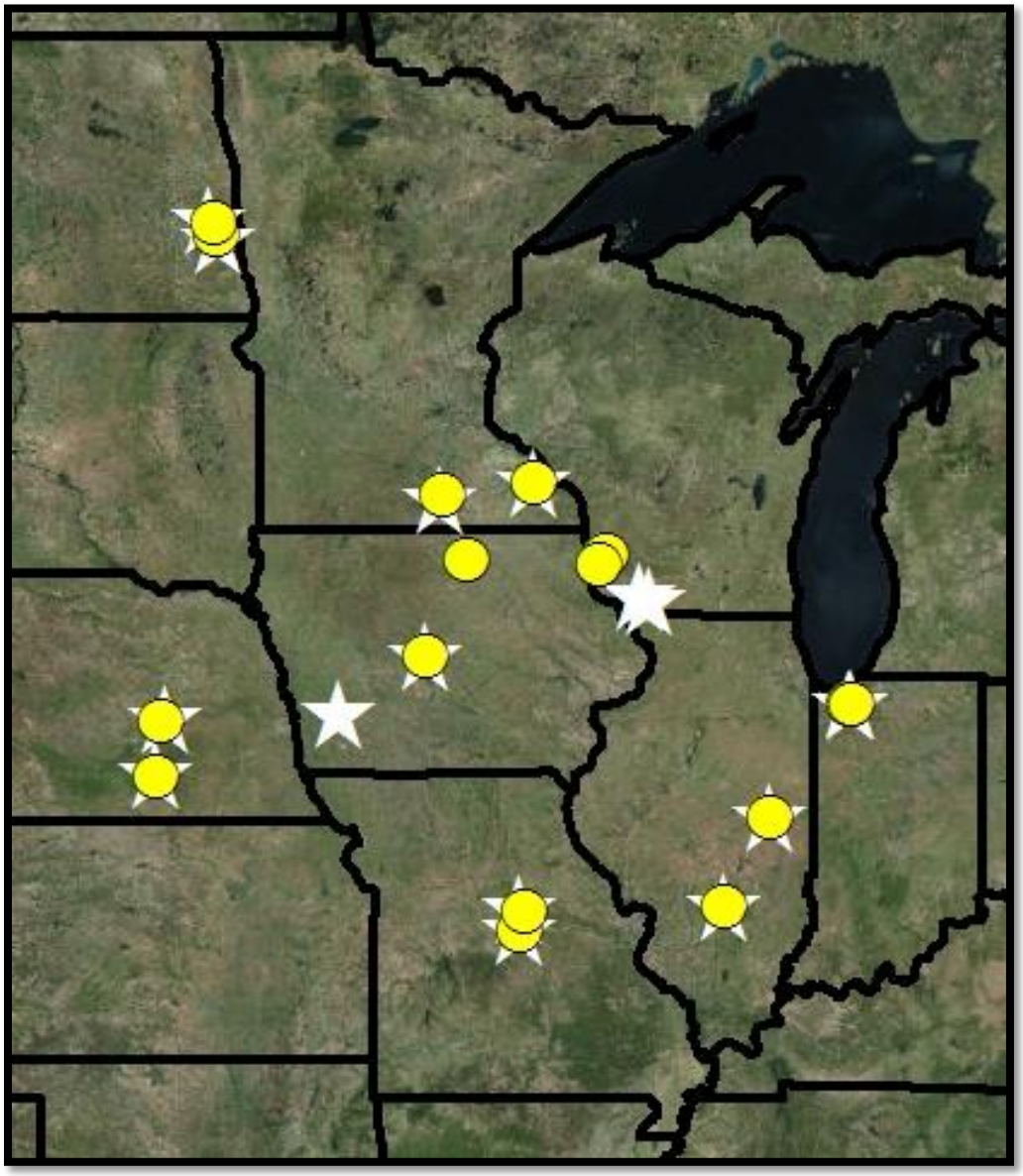

Figure 2.1. Field research sites were located within eight U.S. Corn Belt states (Iowa, Illinois, Indiana, Minnesota, Missouri, Nebraska, North Dakota, and Wisconsin). Each state contained two sites for two growing seasons (2014 - 2015), totaling 32 sites. The 2014 sites are represented by yellow circles while the 2015 sites are represented by white stars.

Table 2.1. Management description for the 16 sites for the 2014 growing-season. Each of the eight participating states chose two sites that contrasted in productivity within the state.

State	Site	Productivity	Previous Crop	Tiled	Irrigated	Tillage†	Hybrid	Seed Rate	Row Space	Planting Date	Sensing Date	Sensing Growth Stage
								seeds/ha	cm			
IA	Ames	Low	SB	No	No	FC	P0987AMX	87,685	76	7 May	26 Jun	V9
IA	Mason	High	SB	Yes	No	No-till	P0636AMX	86,450	76	9 May	9 Jul	V9
IL	Brown1	Low	SB	No	No	FC	P1498AM	79,040	76	24 Apr	13 Jun	V8
IL	Urbana1	High	SB	No	No	FC	P1498AM	86,450	76	25 Apr	15 Jun	V8.5
IN	Loam1	High	SB	No	No	F chis/SP FC	P0987AMX	81,510	76	19 May	27 Jun	V9
IN	Sand1	Low	SB	No	No	F chis/SP FC	P0987AMX	81,510	76	19 May	27 Jun	V9
MN	New1	High	SB	Yes	No	-	P9917AMX	85,215	76	21 May	7 Jul	V9
MN	Charles1	Low	SB	No	No	Vertical-till	P9917AMX	85,215	76	16 May	8 Jul	V10
MO	Bay	Low	SB	No	No	FC	P1498AM	86,450	76	2 May	20 Jun	V10
MO	Troth1	High	SB	No	No	No-till	P1498AM	86,450	76	2 May	21 Jun	V10.5
ND	Amenia1	High	Corn	No	No	F chisel/ FC	P8954AM1	79,040	56	23 May	10 Jul	V8.5
ND	Durbin1	Low	Corn	No	No	F chisel/FC	P8954AM1	79,040	56	23 May	10 Jul	V8.5
NE	Brandes1	Low	SB	Yes	Yes	No-till	P1151HR	86,450	76	19 Apr	26 Jun	V9
NE	SCAL1	High	SB	No	Yes	No-till	P1151HR	79,040	76	7 May	24 Jun	V8.5
WI	Steuben	High	SB	No	No	No-till	P0636AMX	86,450	76	7 May	25 Jun	V9
WI	Wauzeka	Low	SB	No	No	No-till	P0636AMX	79,781	76	6 May	25 Jun	V9

†FC, field cultivated; F, fall; Chis, Chisel; SP, spring.

Table 2.2. Management description for the 16 sites for the 2015 growing season. As done previously, each of the eight participating states chose two sites ranging in productivity of the 2015 growing season.

State	Site	Productivity	Previous Crop	Tiled	Irrigated	Tillage†	Hybrid	Seed Rate	Row Space	Plant Date	Sensing Date	Sensing Growth Stage
								seeds/ha	cm			
IA	Boone	Low	SB	No	No	FC	P0987AMX	86,450	76	18 May	7 Jul	V10
IA	Lewis	High	SB	No	No	FC	P1498AM	85,215	76	29 Apr	7 Jul	V10
IL	Brown2	Low	SB	No	No	SP FC/ F deep ripped	P1498AM	86,450	76	28 Apr	16 Jun	V9
IL	Urbana2	High	SB	No	No	FC / F deep ripped	P0987AMX	86,450	76	23 Apr	15 Jun	V9
IN	Loam2	High	SB	No	No	FC	P0987AMX	80,275	76	29 Apr	17 Jun	V10
IN	Sand2	Low	SB	No	No	No-till	P0987AMX	80,275	76	29 Apr	17 Jun	V10
MN	New2	High	SB	No	No	F FC/ SP FC	P0157AMX	87,685	76	18 Apr	26 Jun	V8
MN	Charles2	Low	SB	No	No	Vertical-till	P0157AMX	85,215	76	1 May	1 Jul	V9
MO	Lonetree	Low	SB	No	No	FC	P1498AM	86,450	76	17 Apr	19 Jun	V9
MO	Troth2	High	SB	No	No	FC	P1498AM	86,450	76	14 Apr	10 Jun	V9
ND	Amenia2	High	Corn	Yes	No	No-till	P9188AMX	83,980	56	24 Apr	14 Jun	V5
ND	Durbin2	Low	Corn	No	No	No-till	P9188AMX	83,980	56	24 Apr	18 Jun	V6
NE	Brandes2	Low	SB	No	Yes	F chisel/ SP FC	P1151HR	86,450	76	19 Apr	29 Jun	V9
NE	SCAL2	High	SB	No	Yes	F chisel/ SP FC	P1151HR	83,980	76	24 Apr	24 Jun	V8
WI	Belmont	Low	SB	No	No	No-till	P0987AMX	90,155	76	4 May	1 Jul	V9
WI	Darling	High	SB	No	No	No-till	P0987AMX	93,119	76	4 May	1 Jul	V9

†FC, field cultivated; F, fall; Chis, Chisel; SP, spring.

Table 2.3. Sixteen different N fertilizer rates split over two times were replicated four times at each site.

Trt #	Planting N	Topdress N	Total N
	——————kg ha^{-1}——————		
1	0	0	0
2	45	0	45
3	90	0	90
4	135	0	135
5	180	0	180
6	225	0	225
7	270	0	270
8	315	0	315
9	45	45	90
10	45	90	135
11	45	135	180
12	45	180	225
13	45	225	270
14	45	270	315
15	90	90	180
16	90	180	270

Table 2.4. Economic optimal N rates, farmer (FarmNR) and algorithm recommended N rates with no N fertilization and 45 N ha^{-1} at planting for all 32 sites in this investigation.

					0 N ha^{-1}			45 N ha^{-1}		
Year	**State**	**Site**	**EONR**	**FarmNR**	**MU Rec**	**HS Rec**	**OSU Rec**	**MU Rec**	**HS Rec**	**OSU Rec**
			---------- kg N ha^{-1} ----------							
2014	IA	Ames	155	224	182	126	85	116	69	73
	IA	Mason	153	180	170	139	63	127	86	58
	IL	Brown	237	180	157	159	65	115	86	59
	IL	Urbana	263	202	156	136	82	117	82	73
	IN	Loam	172	196	129	101	102	105	62	91
	IN	Sand	192	196	125	104	93	105	63	84
	MN	New	158	224	208	168	80	145	100	73
	MN	Charles	117	213	156	125	77	129	89	72
	MO	Bay	177	202	161	129	69	120	80	64
	MO	Troth	188	202	135	110	60	106	63	56
	ND	Amenia	164	224	182	261	62	124	132	56
	ND	Durbin	165	224	222	320	66	169	201	63
	NE	Brandes	205	202	175	179	57	134	112	54
	NE	SCAL	138	186	120	84	73	117	72	72
	WI	Steuben	77	157	156	122	90	117	75	81
	WI	Wauzeka	119	157	153	123	76	113	71	68
2015	IA	Boone	187	224	185	131	93	123	76	81
	IA	Lewis	107	224	155	155	54	118	90	51
	IL	Brown2	124	180	221	146	76	149	90	70
	IL	Urbana2	237	202	141	117	72	118	80	67
	IN	Loam2	160	196	140	112	112	92	0	87
	IN	Sand2	206	196	151	134	100	114	79	88
	MN	New2	151	168	192	147	84	129	84	75
	MN	Charles2	166	213	145	112	91	128	86	86
	MO	Lonetree	314	202	236	168	62	238	142	62
	MO	Troth2	314	224	184	148	79	145	103	74
	ND	Amenia2	155	224	127	190	68	112	64	62
	ND	Durbin2	139	224	139	255	63	123	152	60
	NE	Brandes2	198	202	162	175	56	141	125	55
	NE	SCAL2	27	157	123	93	63	110	67	61
	WI	Belmont	15	246	125	110	77	135	109	79
	WI	Darling	174	224	114	90	70	78	0	58
		Average	167	202	159	146	76	124	87	69

Table 2.5. The mean and RMSE for the difference between the algorithm N recommendation and EONR are presented. Results are presented by growing season and combined over growing seasons. Negative and positive mean values indicate an under- and over-estimation, respectively, in the N rate recommendation. Lower RSME values indicate greater precision.

Target N Treatment	**Year**	**Algorithm**	**Mean**	**RMSE**
kg N ha^{-1}			——kg N ha^{-1}——	
0	2014	MU	-6	53
		HS	-18	72
		OSU	-93	104
		Farmer NR	54	70
	2015	MU	-8	69
		HS	-24	84
		OSU	-91	120
		Farmer NR	64	104
	Combined	MU	-7	62
		HS	-21	78
		OSU	-92	113
		Farmer NR	59	88
45	2014	MU	-45	66
		HS	-77	94
		OSU	-99	110
		Farmer NR	54	70
	2015	MU	-39	81
		HS	-82	116
		OSU	-97	125
		Farmer NR	64	104
	Combined	MU	-42	74
		HS	-80	106
		OSU	-98	118
		Farmer NR	59	88

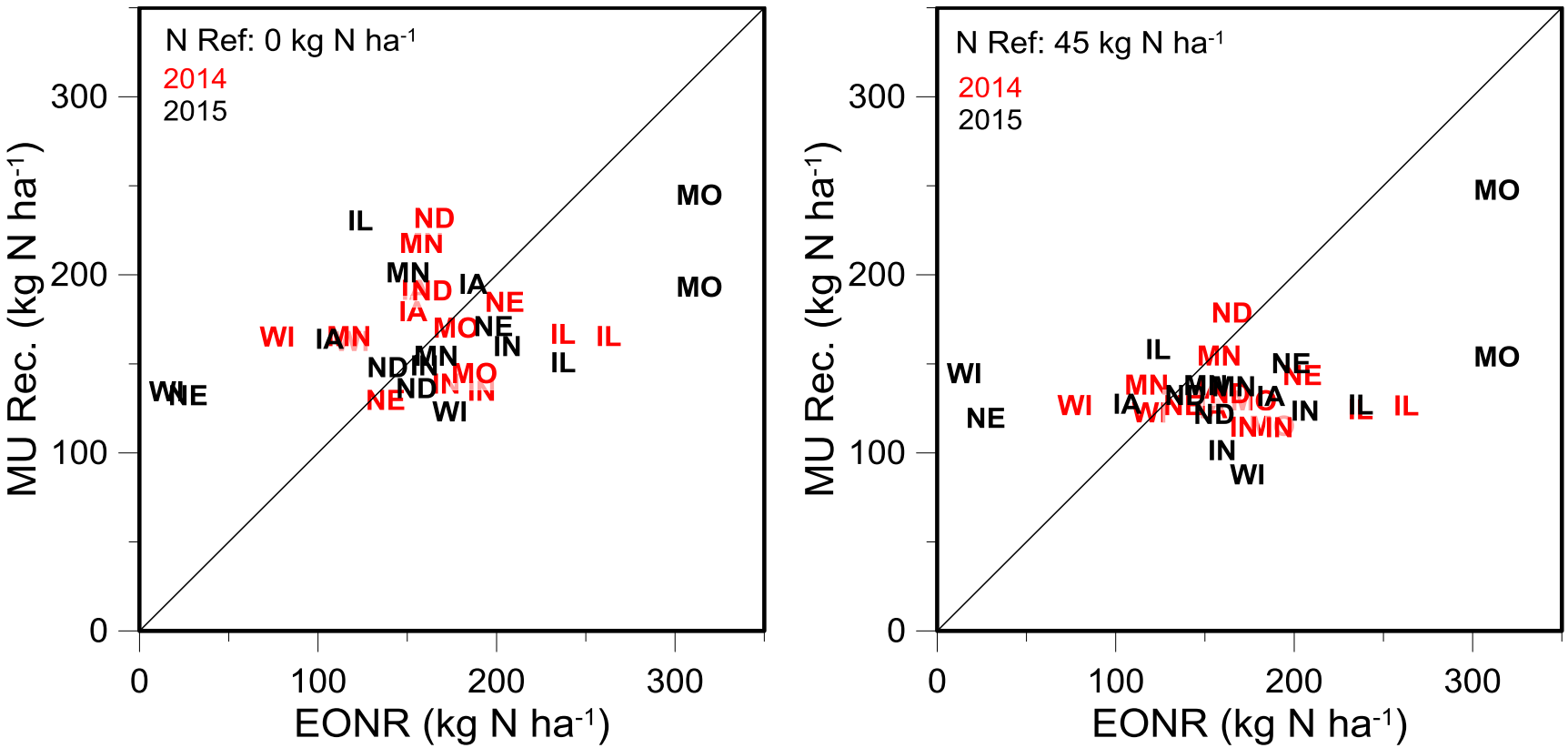

Figure 2.2. The University of Missouri (MU) algorithm N fertilizer rate recommendation (MU Rec.) for 32 sites over two growing seasons for corn receiving no N at planting (left) and corn receiving 45 kg N ha-1 at planting (right) related to the economic optimum N rate (EONR). Points on or near the 1:1 diagonal line indicate the algorithm performed well for making an N rate recommendation. Points below the line represent a recommendation that underestimated N need and sites above the line represent an over-estimated N recommendation. Recommendations were generally higher and better performing (see Table 2.4) when target corn received no N at planting versus corn fertilized with 45 kg N ha^{-1} at planting. This shift would be expected since crop unfertilized at planting would by the V9 growth stage show more N deficiency, and is evidence of the responsiveness of the sensor and algorithm to reflectance values of the corn canopy.

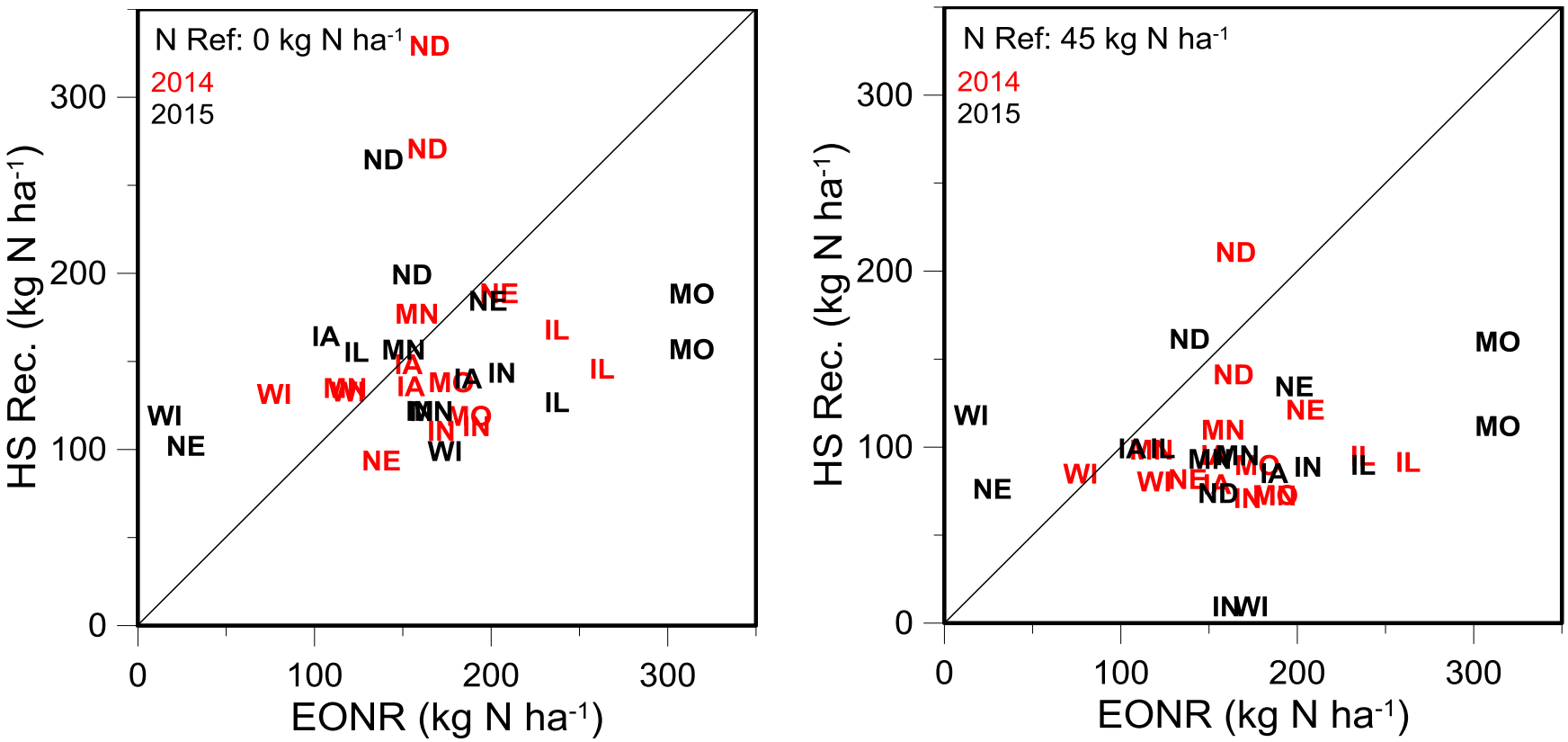

Figure 2.3. The Holland Scientific (HS) algorithm recommended N fertilizer rate (HS Rec.) for 32 sites over two growing seasons for corn that received no N at planting (left) and corn that received 45 kg N ha-1 at planting (right) related to the economic optimum N rate (EONR). Points on or near the 1:1 diagonal line indicate the algorithm performed well for making an N rate recommendation. Points below the line represent a recommendation that underestimated N need and sites above the line represent an over-estimated N recommendation. Similar to the MU algorithm, recommendations were generally higher and better performing (see Table 2.4) when target corn received no N at planting versus corn fertilized with 45 kg N ha^{-1} at planting. This shift would be expected since crop unfertilized at planting would by the V9 growth stage show more N deficiency, and is evidence of the responsiveness of the sensor and algorithm to reflectance values of the corn canopy.

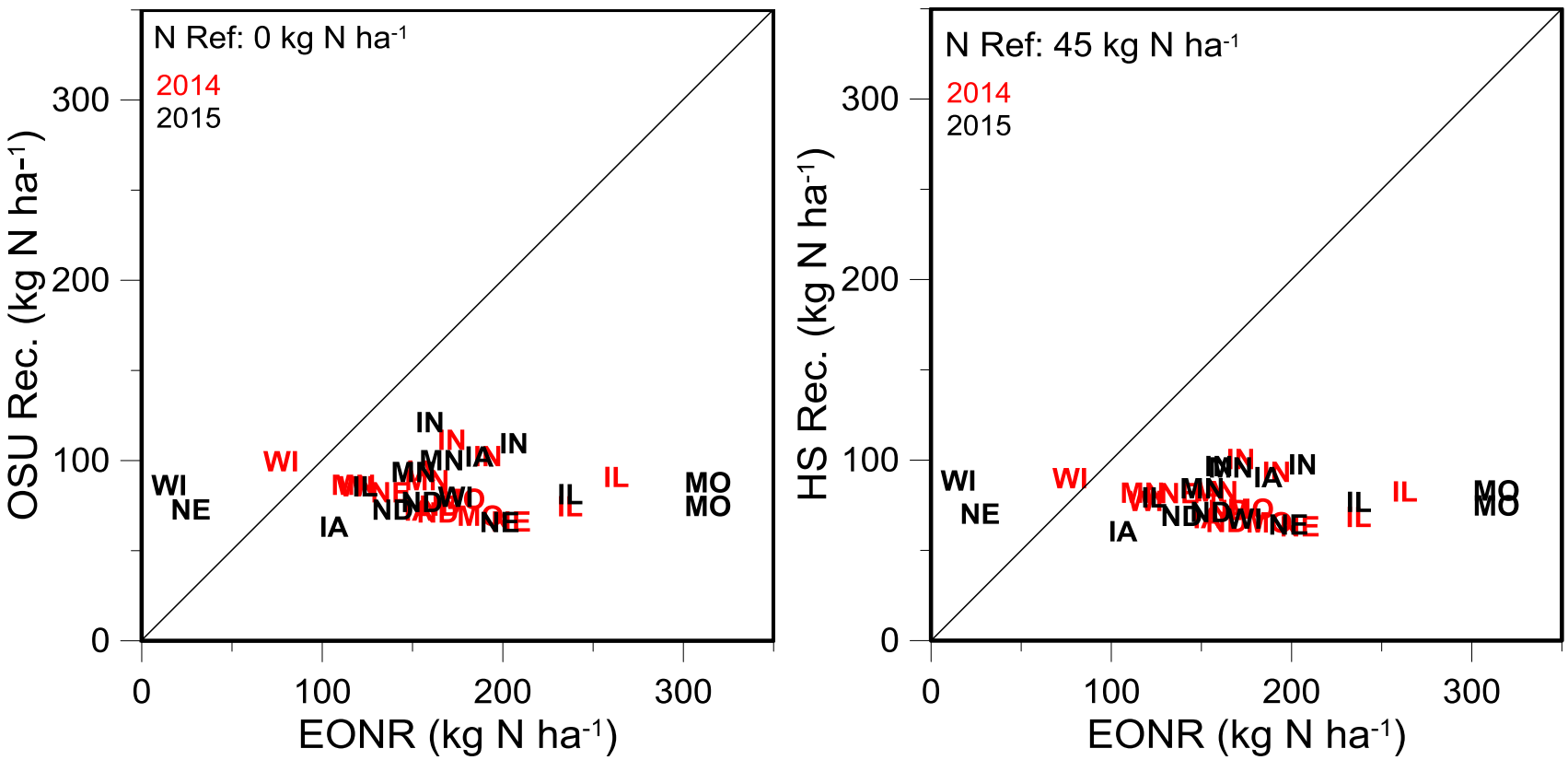

Figure 2.4. The actual Oklahoma State University (OSU) algorithm N fertilizer rate recommendations (OSU Rec.) for 32 sites over two growing seasons for corn that received no N at planting (left) and for corn that received 45 kg N ha-1 at planting (right) related to the economic optimum N rate (EONR). Points on or near the 1:1 diagonal line indicate the algorithm performed well for making an N rate recommendation. Points below the line represent a recommendation that underestimated N fertilizer need and sites above the line represent an over-estimated N recommendation. Recommendations were similar in performance (see Table 2.4) when target corn received no N at planting versus corn fertilized with 45 kg N ha^{-1} at planting. This may demonstrate the OSU algorithms dull sensitivity to changes in reflectance values.

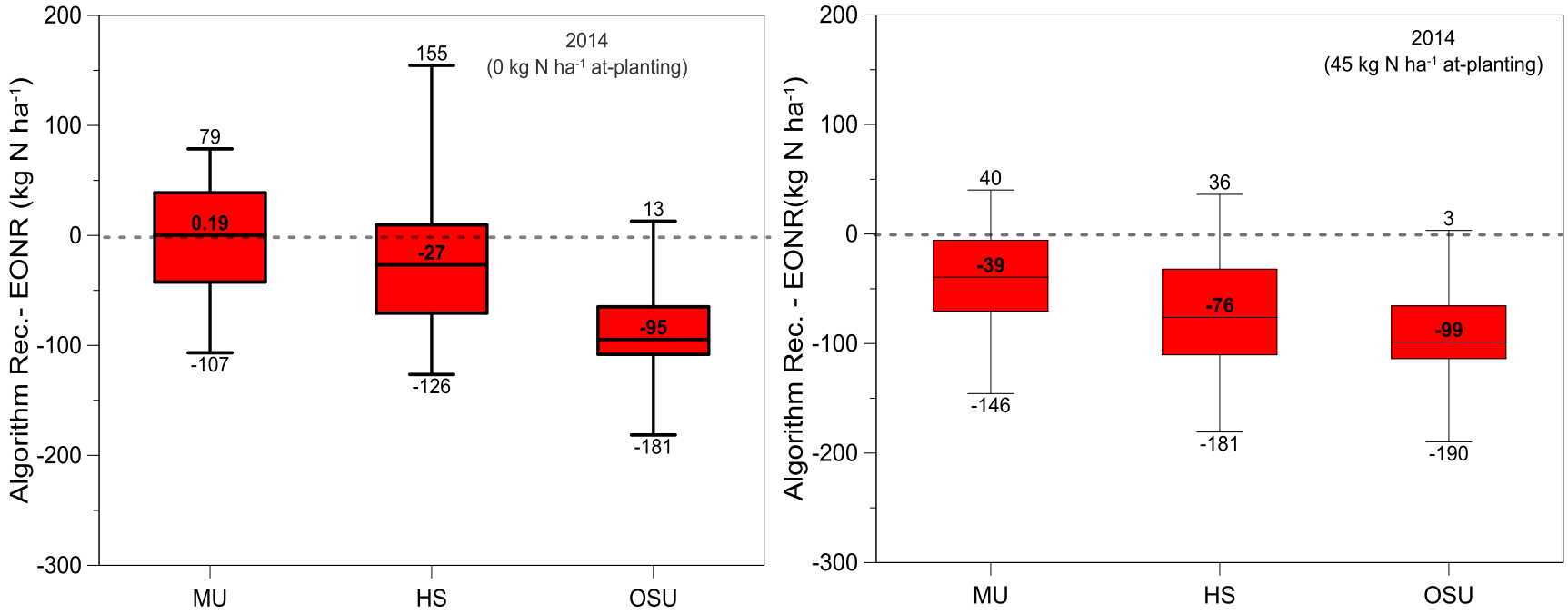

Figure 2.5. Difference between EONR and the N recommendations for 16 sites during the 2014 growing season, contrasting three algorithms with no N applied at planting (left graph) and 45 kg N ha-1 (right graph). Accuracy is represented by alignment of the box median line to a difference = 0. Precision is represented by box size and whisker length. At both N rates, the University of Missouri (MU) algorithm performed the best followed by the Holland Scientific algorithm and then the Oklahoma State University algorithm. A clear improvement in accuracy and precision was found going from the 45 kg N ha^{-1} to the 0 kg N ha^{-1} at-planting fertilizer rates. Median values for all algorithms were lower with the 0 kg N ha^{-1} N fertilizer compared to the 45 kg N ha^{-1} rate.

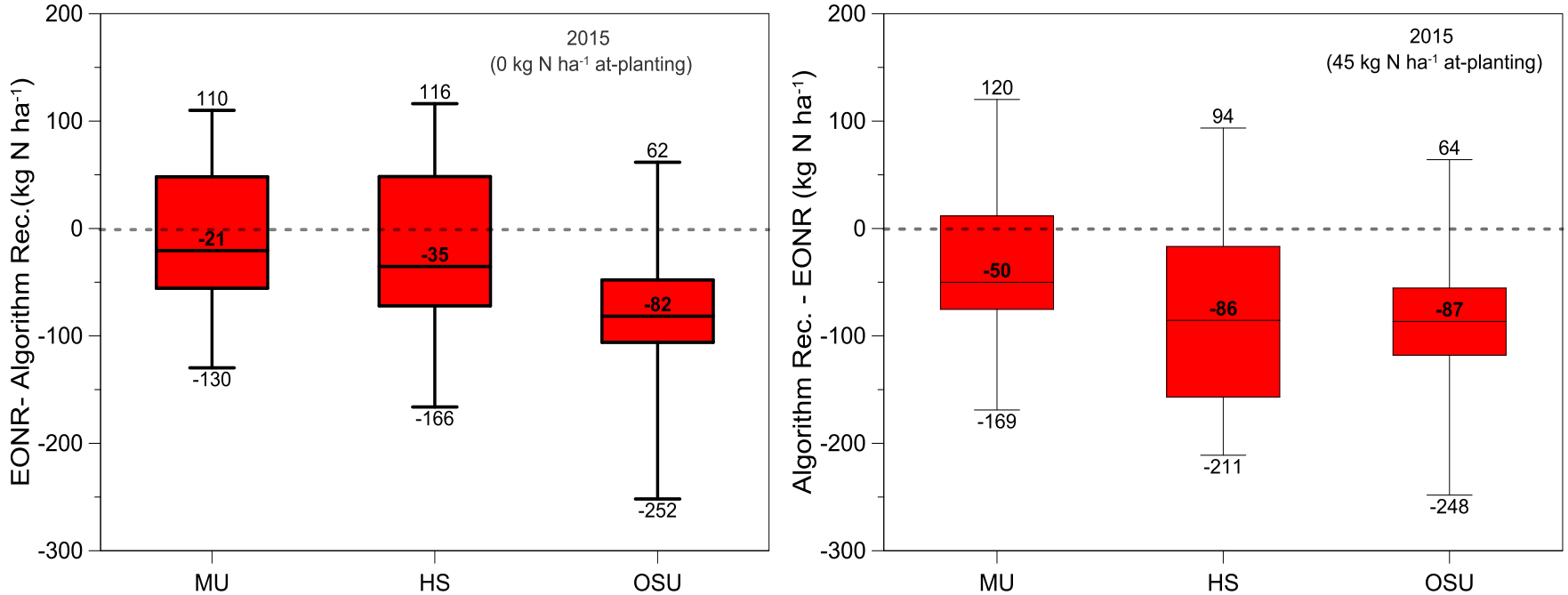

Figure 2.6. Difference between EONR and the N recommendations for 16 sites during the 2015 growing season, contrasting three algorithms with no N applied at planting (left graph) and 45 kg N ha-1 (right graph). Accuracy is represented by alignment of the box median line to a difference = 0. Precision is represented by box size and whisker length. At both N rates, the University of Missouri (MU) algorithm performed the best followed by the Holland Scientific algorithm and then the Oklahoma State University algorithm. A clear improvement in accuracy and precision is seen between the 45 kg N ha^{-1} and 0 kg N ha^{-1} at-planting fertilizer rates. Median values decreased for all algorithms when using the 0 kg N ha^{-1} N fertilizer rate as the target. When compared to the 2014 growing season, algorithm performance declined in both accuracy and precision.

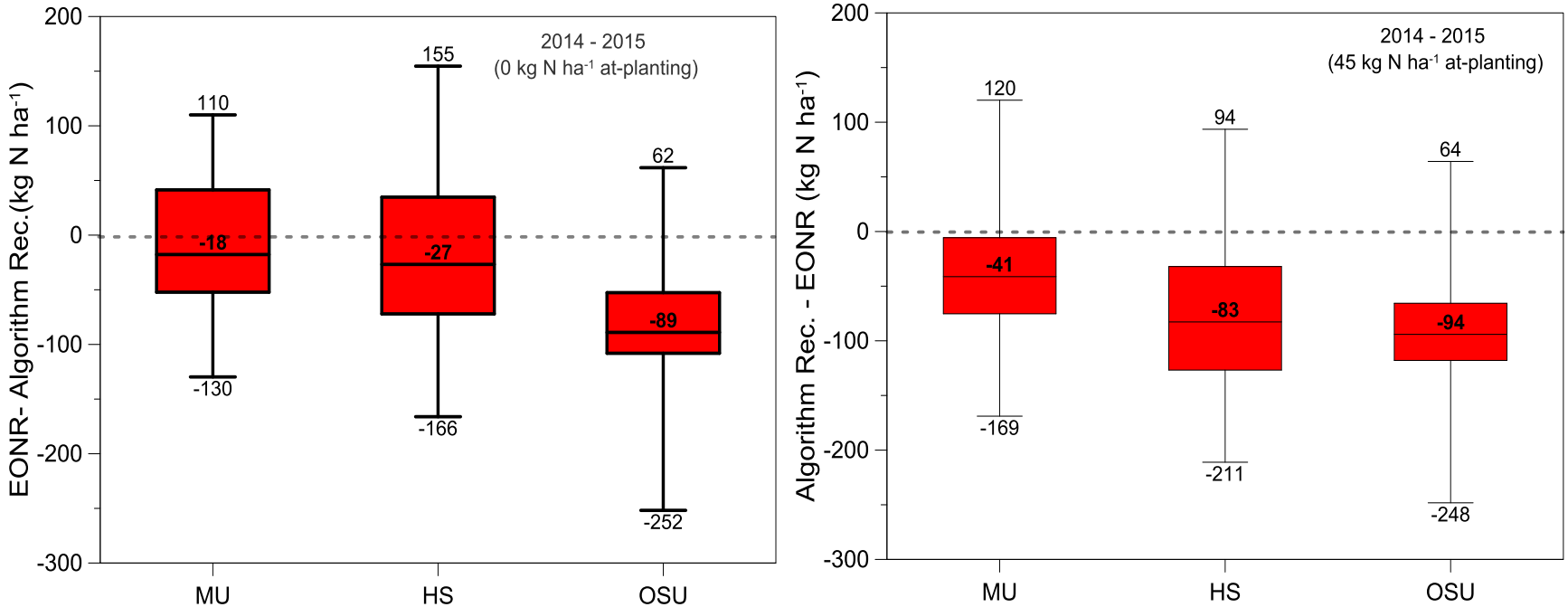

Figure 2.7. Difference between EONR and the N recommendations for 32 sites during the 2014 and 2015 growing seasons, contrasting three algorithms with no N applied at planting (left graph) and 45 kg N ha-1 (right graph). Accuracy is represented by alignment of the box median line to a difference = 0. Precision is represented by box size and whisker length. At both N rates, the University of Missouri (MU) algorithm performed the best followed by the Holland Scientific algorithm and then the Oklahoma State University algorithm. A clear improvement in accuracy and precision is seen between the 45 kg N ha^{-1} and 0 kg N ha^{-1} at-planting fertilizer rates. Median values decreased for all algorithms when using the 0 kg N ha^{-1} N fertilizer rate as the target. The OSU algorithm improvement from the 45 kg N ha^{-1} to 0 kg N ha^{-1} at-planting is not as severe when compared to the MU and HS algorithms. This suggests a lack of sensitivity to the changes in reflectance values.

Table 2.6. Precipitation (PPT) from planting to topdress (TP) and from TP to plant maturity (PM) for all 32 sites. The amount of irrigation was included in PPT for sites with irrigation.

Year	State	Site	PPT from Planting - TP	PPT from TP to PM
			————————cm————————	
2014	IA	Ames	25	49
	IA	Mason	33	14
	IL	Brown	22	33
	IL	Urbana	27	40
	IN	Loam	25	39
	IN	Sand	28	20
	MN	New	28	18
	MN	Charles	24	6
	MO	Bay	17	17
	MO	Troth	15	10
	ND	Amenia	14	13
	ND	Durbin	16	12
	NE	Brandes	28	22
	NE	SCAL	23	31
	WI	Steuben	22	27
	WI	Wauzeka	25	25
2015	IA	Boone	21	42
	IA	Lewis	25	26
	IL	Brown2	21	36
	IL	Urbana2	16	28
	IN	Loam2	33	28
	IN	Sand2	15	33
	MN	New2	32	38
	MN	Charles2	22	28
	MO	Lonetree	33	36
	MO	Troth2	17	28
	ND	Amenia2	22	20
	ND	Durbin2	13	14
	NE	Brandes2	20	24
	NE	SCAL2	41	12
	WI	Belmont	19	12
	WI	Darling	22	27

Chapter 3: Regional Analysis of Yield Response and Economic Optimum Nitrogen Rate Relative to Soil and Weather Factors

3.1 Abstract

Corn production across the US Cornbelt can be often limited by the loss of nitrogen (N) due to leaching, volatilization and denitrification. These processes are affected by numerous soil characteristics and weather variables making it difficult to know when and how much N fertilizer is needed to obtain the economic optimum N rate (EONR). This chapter summarizes the relationship between select soil and weather variables with corn yield response to N (ΔYield) and EONR. Nitrogen response trials were conducted across eight states, totaling 32 sites over two growing seasons (four per state) with soils ranging in productivity. Measured and USDA SSURGO soil properties were obtained and analyzed on three depth increments (0-30, 0-61, and 0-92 cm). Weather information used was from planting to topdress (~V9). Few soil and weather variables were found significant in the final models selected for ΔYield and EONR. These had low r^2 vales (<0.20). For example, as soil organic matter increased ΔYield decreased. As clay, precipitation, and abundant and well-distributed rainfall increased ΔYield increased. With EONR, only the Shannon Diversity Index (SDI) remained in the final model with EONR increasing with higher SDI values. Complex and variable N-transformation factors across such a large area as this study represent a major reason only weak relationships were found with soil and weather properties. However, the soil and weather information found significant here may be able to better inform adaptive N

management tools for making in-season N fertilizer recommendations such as canopy reflectance sensors.

3.2 Introduction

Successful N management in corn (*Zea mays* L.) is accomplished by applying the correct amount of N fertilizer needed to reach the economic optimal N rate (EONR) while minimizing N lost to the environment. To ensure maximum yield, N fertilizer is commonly over-applied resulting in poor N use efficiency, as well as ground and surface water pollution (Tremblay et al., 2012; Schröder et al., 2000; Shanahan et al., 2008). Measured spatial variability of soil characteristics and variation in year-to-year weather factors make it difficult to determine the correct amount of N fertilizer needed to reach EONR. Since corn N uptake is minor early in the growing season, and because of the uncertainty associated with weather, producers sometimes wait until mid-season to apply additional N fertilizer.

Corn N fertilizer recommendations have historically been based on expected grain yield (Blackmer et al., 1992; Gehl et al., 2005), without considering N response to soil and weather conditions. It is well documented that soil and weather metrics have all been related to corn N response (Xie et al., 2013, Tremblay et al., 2012). Furthermore, it has been observed that corn N response as measured by the yield increase with N fertilization, is significantly related to EONR (r^2 = 0.52; Meisinger et al., 2008). Understanding weather and soil property variability, and their relationship to crop

response measurements can be used to improve in-season N fertilizer recommendations and help prevent environmental pollution.

Spatial diversity at sub-field to regional scales of soil texture, soil organic matter (SOM), and plant available water (PAWC) combined with varying total rainfall, the evenness of rainfall, and temperature contribute to the complexities of N fate in crops and the environment. Multiple N loss processes and pathways can exist in any field. Significant denitrification (the conversion of NO_3^- to N0x and N_2 gases) most often occurs in clayey textured soils experiencing anaerobic soil conditions from excessive rainfall and with warm soil temperatures (Blevins et al., 1996). In contrast, NO_3^- leaching below the rooting depth results when large amounts of rainfall occur and especially on soils with low water holding capacity or coarse textured soils (Power et al., 2001). Volatilization, (the loss of N through ammonia-NH_3 gas), may also occur if certain N fertilizers, such as urea, are not incorporated into the soil (Ma et al., 2010). These interactions result in varying field conditions, thus requiring different methods of N management. Research is needed to decide how these soil and weather variables can aid in making better N fertilizer recommendations.

Weather (precipitation and temperature) generally drives plant growth and influences soil conditions (Tremblay and Bélec, 2006), which ultimately influence corn yield. Monthly rainfall has been proven to affect corn yield variability (Teigen and Thompson, 1995). Corn has been generally found to respond more to applied N fertilizer during years of above-average rainfall when compared to years of below-average

rainfall (Yamoah et al., 1998). Additionally, corn yield response to N fertilization across North America was found to be most affected by precipitation during June and July, as well as by temperatures during July and August (Jeutong et al., 2000). Some have identified the distribution or evenness of rainfall as being significant in describing responsiveness to N fertilizer, thus affecting yield (Shaw, 1964; Reeves et al., 1993; Tremblay et al., 2012). For example, frequent rainfall events were observed in 51 studies from 2006 to 2009 in several North American locations and were explained to have a large amount of soil moisture early in the growing season that promoted N loss through denitrification and leaching, as well as increased responsiveness to N fertilizer (Tremblay et al., 2012). Rainfall and temperature are generally accepted as metrics directly impacting yield-limiting soil factors of oxygen levels, biological activity, decomposition of organic matter to soil mineral N, nutrient availability, plant-available water, and ultimately crop yield (Power et al., 2001; Tremblay, 2004; Tremblay and Bélec, 2006; Kyveryga et al., 2007; Shanahan et al., 2008; Tremblay et al., 2012).

Soil texture effects soil water flow, available N, plant-available water content (PAWC), the transportation and availability of ions (Schaetzl and Anderson, 2014), and crop yield (Zhu et al., 2009; Armstrong et al., 2009; Tremblay et al., 2012). While conflicting results exist, corn yield is generally greater on coarse-textured soils during wet years than during dry years. Also, corn yields tend to be greater on fine-textured soils during dry years than during wet years (Tremblay et al., 2011). Fifty-seven studies on smallholder farms in sub-Saharan Africa demonstrated the effect of soil texture on N fertilizer response. Nitrogen response was found to be larger on clay soils compared to

loam or sandy soils (Chivenge et al., 2011). Similarly, in North America, finer textured soils were found to respond more to N fertilizer (Tremblay et al., 2012). Soil organic matter has also proven to be related to corn yield; soil organic matter makes up a small percentage of the total soil volume (<5%) but has a large effect on other soil properties (Sylvia et al., 2005). As SOM increases, soil aggregation improves, water infiltration rates rise and aeration increases. Collectively, these effects ultimately improve growing conditions.

Soil information can be obtained from different sources. Through the USDA-NRCS Soil Survey Geographical database (SSURGO), the most used conventional soils database in the United States (Yang et al., 2011), most of the previously mentioned soil variables can be obtained. The accuracy and precision of SSURGO information is affected by mapping techniques, the level of spatial detail, and the exactitude of soil attributes (Zhu, 1997; Zhu et al., 2001). Efforts to verify SSURGO reports with actual soil measurements have been contradictory. Field-truthing of SSURGO reports on the Hunewell ranch in Erath County, Texas showed poor relationships between SSURGO estimated soil texture and pH to actual samples (Zylman et al., 2015). Variation between SSURGO and the collected samples was greatest in erosional areas and transitional areas between SSURGO mapping units. However, research performed on forested soils in the northern Appalachian Plateau of Pennsylvania comparing horizon type, color, percentage of rock fragments, textural class, structure, and acidity between actual soil measurements and the original NRCS report found 80% of the plots evaluated matched the original report. Differences found between field measurements and NRCS

descriptions were attributed to dissimilarities in mapping models, changes in topography, field personnel, and the knowledge available to them at the time of the original description. Research is needed to compare SSURGO described agricultural soils with actual field measured soil properties (Drohan et al., 2003) and to determine if either can be related to corn N response or EONR.

The objectives of this research were to determine if soil and weather information from planting to topdress could be related to corn yield N response (ΔYield) and EONR across a regional landscape. A sub-objective of this research was to compare SSURGO soil properties with measured soil properties.

3.3 Materials and Methods

3.3.1 Research Sites and Locations

This research was conducted as part of public-private collaboration between eight major land-grant universities (University of Iowa, University of Illinois, University of Indiana, University of Minnesota, University of Missouri, North Dakota State University, University of Nebraska, and the University of Wisconsin) within the US Corn Belt and DuPont Pioneer. This project is commonly referred to as the, “Performance and Refinement of Nitrogen Fertilization Tools” project. The approach for this research was fundamental N fertilizer rate response field-plot studies conducted with standardized protocols and methods across a wide range of soil and weather conditions. Yield and soil measurements from these plot studies provided both the measurements needed as well as N response functions.

Thirty-two corn N response trials were conducted during 2014 to 2015 in eight Midwestern Corn Belt States. In each state, two sites ranging in productivity were selected for each growing season, giving four sites per state (Figure 3.1). Productivity was determined by historical yield and general soil productivity. Research sites were planted at a target population of 86,450 plants ha^{-1} using Pioneer hybrids (DuPont Pioneer, Johnstown, IA) found suitable for the selected sites within the region. Most research sites followed soybean, however four sites followed corn. The MN, New site and the IA, Mason site were tiled. Both NE sites were irrigated and all but three sites received at least some form of tillage. Planting dates ranged from April 19 – May 23 and topdress dates ranged from June 7 – July 10. Descriptions of management for all sites over the two growing seasons are presented in Tables 3.1 and 3.2.

3.3.2 Plots and Treatments

Plot dimensions were state and site dependent and were determined by the planting (planter width) and harvesting (combine width) equipment available, but minimal plot harvest area was 18.6 m^2. Average size per site was 0.4 ha. Sixteen different N rate treatments, replicated four times (totaling 64 plots per site), were used in a randomized complete block design (Table 3.3). Nitrogen treatments were obtained using dry-prilled NH_4NO_3-N fertilizer broadcast applied. The “at-planting” fertilizer was applied within 48 hours of initial planting while the topdress fertilizer was applied between the V8 to V10 growth stages. Treatment one was the non-fertilized control. Treatments 2 to 8 received all N at-planting in 45 kg N ha^{-1} increments from 45 to 315 kg N ha^{-1}, while treatments 9 to 14 received 45 kg N ha^{-1} at-planting and the rest at

topdress in 45 kg N ha^{-1} increments from 45 to 270 kg N ha^{-1}. Treatments 15 and 16 received 90 kg N ha^{-1} at-planting with the remaining N at topdress.

3.3.3 Soil and Weather

Both measured soil measurements and SSURGO data were gathered for all sites and years. Soil EC_a surveys were performed one to four weeks prior to planting using a Veris 3100 (Veris Technologies, Salina, KS). Sensing was performed on 4.5 m spacing travelling 5 kph across the plot area. Perpendicular passes were made through the plot area to aid in the creation of an interpolated map.

For soil characterization two adjacent 1.2 m deep soil cores with a diameter of 4.76 cm were obtained from each of the four replications at each site using a Giddings Model #5-UV / MGSRPSUV (Giddings Machine Company, Windsor, CO). The location of both soil cores in each replication was determined using the soil EC_a survey map performed just prior to sampling, such that core sites represented the range of soil differences within a site as observed by soil EC_a. Both drilled cores were laid side-by-side and characterized and separated by horizon. One core was used to calculate bulk density (BD) and soil moisture while the other was processed and sent to the University of Missouri Soil Health Assessment Center for additional property analyses. Analyses included the following: particle size determination through the pipette method, cation exchange capacity (CEC), total carbon, total organic carbon, total inorganic carbon, SOM, pH (salt and water), and BD. Amount of clay (i.e. %clay) was calculated by using the particle size determination (R. Burt and Soil Survey Staff, 2014; Nelson and

Sommers, 1996). Plant Available Water Content was determined using the Saxton and Rawls formula (Saxton and Rawls, 2006). This equation uses measured sand and clay textural information along with SOM to determine soil moisture at both the permanent wilting point and field capacity. The difference between the soil moisture at field capacity and permanent wilting point results in PAWC. Following this analysis, the four cores from each site were averaged together to obtain site-level data.

The SSURGO data for each site was obtained from the National Resource Conservation Service (NRCS) via the "Web Soil Survey" website and the "Soil Data Viewer" plug-in available in ArcMap (Esri, Redlands, CA). If more than one SSURGO mapping unit was assigned to the 0.4 ha research site, the most dominant SSURGO mapping unit was chosen. Soil variables collected from SSURGO included SOM, %clay, and PAWC.

Soil organic matter, PAWC, and clay content values collected from SSURGO and the University of Missouri's Soil Health Assessment Center were depth-weighted to three intervals of 0-30cm, 0-61cm, and 0-91cm.

Each site's weather data were collected using a HOBO U30 Automatic Weather Station (Onset Computer Corporation, Bourne, MA). Daily temperatures were used to calculate growing degree days (GDD) while daily precipitation (and irrigation), in conjunction with the Shannon Diversity Index (a measure of eveness; SDI) was used to calculate a measure called abundant and well-distributed rainfall (AWDR; Tremblay et al., 2012). These variables were calculated using the equations below:

$$GDD = \frac{T_{Max}+T_{Min}}{2} - T_{Base} \quad [1]$$

where T_{Max} = maximum daily temperature, T_{Min} = minimum daily temperature and T_{Base} = 10^0 C. All temperature values were measured in degrees Celsius (^{0} C).

$$SDI = \left[-\sum pi \frac{\ln(pi)}{\ln(n)}\right] \quad [2]$$

where pi = daily rainfall/total precipitation and n = number of days in the specified time period being used.

$$AWDR = SDI \times Total\ Precipitation \quad [3]$$

where precipitation and AWDR are measured in cm. Weather data used in the analysis were collected between the dates of planting and topdress.

3.3.4 Evaluation and Statistics

Data were analyzed by site using SAS version 9.2 (SAS Institute Inc., Cary, NC). The EONR was calculated using, a quadratic-plateau function since it has generally been found to be the best model in describing corn yield response to N (Scharf et al., 2005; Cerrato and Blackmer, 1990). Proc NLIN in SAS 9.2 was used to fit the data to the quadratic-plateau function. The EONR (kg N ha^{-1}) was calculated for all 32 site years using treatments 1, 2, and 9-14 (Table 3.3) as shown:

$$EONR = \frac{(-b-(ratio)}{(2c)} \quad [4]$$

where *b* and *c* = linear and quadratic response coefficients from optimized quadratic function, and ratio = \$0.88 kg^{-1} N/\$0.03 kg^{-1} grain (i.e., N price/corn price). The EONR was set to not exceed the maximum N rate (315 kg N ha^{-1}).

Delta yield (Mg ha^{-1}), or the increase in yield by N fertilizer application to EONR was calculated across all 32 sites (Table 3.3) as shown:

$$\Delta Yield = Eq.[4] - grain\ yield\ with\ no\ N\ fertilizer\ applied \qquad [5]$$

Linear regression, was performed for all soil (at all three depth intervals) and weather variables, using the Proc REG function in SAS 9.2, to determine which were significant ($p < 0.10$) when evaluated relative to ΔYield and EONR. The linear two-way interactions between these variables were also modeled using regression ($p < 0.10$). All significant simple and two-way variables were then included in a Proc GLMselect function in SAS 9.2. The procedure selects the best variables ($p < 0.10$) within a cross-validation modeling procedure to explain variation in ΔYield and EONR.

3.4 Results and Discussion

Values of ΔYield and EONR for the 32 sites are presented in Table 3.4. Delta yield ranged from as little as 0.3 to 9.8 Mg ha^{-1} with the mean and median of 5.9 and 6.2 Mg ha^{-1}, respectively. By year, the mean ΔYield of 2014 was 0.4 Mg ha^{-1} larger than 2015. EONR ranged from as little as 15 to 314 kg N ha^{-1} with the mean and median of 167 and 165 kg N ha^{-1}, respectively. By year, the mean EONR of 2014 was nearly identical to 2015 (0.4 kg N ha^{-1} difference). Season long precipitation ranged from as little as 25 to 74 cm

with the mean and median of 48.5 and 49 cm, respectively. By year, the mean precipitation of 2014 was 4 cm lower than 2015.

Corn yield response to N fertilization was examined relative to weather information obtained from planting to topdressing (~V9) along with soil properties. Corn response to added N was related to SSURGO surface (0-30 cm) soil clay (clay1) content interacting with precipitation and by clay1 interacting with AWDR (soil values in Table 3.4 and significance in Table 3.5).Delta yield was observed to increase with greater precipitation and precipitation evenness, but the increase diminished as clay decreased (Figure 3.2). The relationship is similar to that found in previous investigations (Tremblay et al., 2012; Yamoah et al., 1998) where the explanation is that on soils with more clay under wetter conditions N yield potential is greater than coarser-textured sols. This supports previous claims (Tremblay et al., 2012) that as clay, precipitation, and AWDR increase, conditions favor N loss through denitrification and therefore result in increased responsiveness to N fertilizer application (Figure 3.2).

Corn response to added N was also influenced by measured surface (0-30 cm) SOM (soil values in Table 3.4 and significance in Table 3.5). This was the only measured soil variable found related, and it was weakly significant (Figure 3.3). Delta yield slightly decreased as SOM increased. Stated differently, the magnitude of yield increase in response to N diminished as SOM increased. A larger amount of SOM implies greater amounts of soil N, lowering the responsiveness to added N fertilizer. However, several sites having similar amounts of SOM responded to N differently. These sites include

Urbana, SCAL2, Belmont, and Darling. The Urbana site was highly responsive to N (ΔYield = 9.8 Mg ha^{-1}) while the other three sites mentioned were not (<3.2 Mg ha^{-1}). This suggests other factors are influencing the interaction between added N fertilizer and final yield. One such factor affecting the SCAL2 site may have been the early October hail storm in 2014 that left most of the soybean (Glycine max *L.*) crop on the ground which likely served as a slow release source of N for the 2015 corn crop. Though not analyzed by year, the clustering of 2015 observations generally above 2014 observations in Figure 3.3 illustrates the uniqueness of growing seasons, particularly since many of the sites between the two years are nearly co-located (Figure 3.1). The figure also shows that 2014 observations appear to contribute more to the relationship between ΔYield and SOM. Previous studies document well the impact SOM has to ΔYield (Xie et al., 2013). The cation exchange capacity, soil aggregation, water infiltration, and aeration increase with increased SOM (Sylvia et al., 2005) likely caused the relationship observed here.

The weak relationship between ΔYield and SOM found in this investigation may be due to variations in the microbiology of soils that would be present over such a wide regional scale. The decomposition of SOM and the mineralization of N are largely dependent on soil microorganisms (Sylvia et al., 2005). Soil microorganisms are affected by weather, temperature, soil aeration, and soil carbon, as well as the amount of N fertilizer added to soils (Sylvia et al., 2005). Therefore, fields that have similar amounts of SOM may respond to added N differently. The MN, New site had twice as much SOM as the WI, Wauzeka site but responded to added N similarly, suggesting other

interactions are affecting corn N response. The WI, Belmont and IA, Boone sites had nearly identical SOM, however the responsiveness to added N was vastly different. The IA, Boone site had a ΔYield of 7.7 Mg ha^{-1} while the ΔYield of the WI, Belmont site was 0.3 Mg ha^{-1}. These differences may be a result from rainfall following topdress or other soil properties interacting with N.

3.4.1 Economic Optimum N Rate

The EONR for the 32 sites were also examined relative to weather and soil properties. The SDI was the only soil or weather measurement that was related to EONR (Table 3.6; Figure 3.4). Economic optimal N rate increased with evenness of rainfall. These results help support the idea that distribution of rainfall events help preserve soil moisture and promote crop growth and therefore N need. Therefore, the SDI may be able to aid in making a more informed in-season N fertilizer recommendation.

The lack of other significant soil and weather variables may be attributed to several factors. Spatial and temporal heterogeneity found within the geographical region of this study was substantial which resulted in a large range of EONR values. This increased the complexity of relating soil and weather characteristics directly to EONR. No two fields have the same conditions; added to that the behavior of field varies from one growing season to the next due to weather changes (Kitchen et al., 2005). Research has shown that seasonal weather impacts corn production more than spatial variability (Dinnes et al., 2002; Power and Weise, 2001). Some have found weather before topdress N applications to be the most influential factor in determining N fertilizer

response (Xie et al., 2013), while others have observed weather following topdress N applications to be most significant in determining N fertilizer response and EONR (Sogbedji et al., 2001; Kahabka et al., 2004). Perhaps stronger relationships would be found if a larger window of temperature and rainfall information were considered. While this may be true, the widespread adoption of applying N even later in the season than that done in this investigation is unlikely unless late in-season strategies prove successful. Foul weather, imperfect soil conditions, and potential mechanical problems may arise shrinking the time available to apply N fertilizer.

3.4.2 Other Considerations

The soil and weather factors found to be important in this study may also help explain the difference found between N fertilizer recommendation tools, such as canopy sensors, and EONR. Canopy sensors can detect local within-field spatial variability through light reflectance, but do not account for soil or weather inputs (Kitchen et al., 2010; Tremblay et al., 2012). The fusion between canopy sensor information and spatial and temporal information like weather and soil properties may improve in-season N fertilizer applications.

When comparing SOM, the variability among corn response to added N was better explained through the interaction between clay1 and total precipitation, and the interaction between clay1 and AWDR. However, these variables are highly correlated (R^2 = 0.93), partially accounting for the same variability. These results suggest SSURGO and measured soil variables may be similar in their ability to account for variability among

ΔYield. No soil measurement, either SSURGO or measured, were related to EONR. As previously stated, these SSURGO and actual soil measurements may aid in explaining the difference found between N fertilizer recommendation tools and EONR.

3.5 Conclusion

The importance of soil and weather variability on ΔYield has been widely studied extensively using various methods. This study evaluated the relationship between ΔYield, EONR, and soil and weather data over 32 locations. Results showed that SOM, the interaction between total precipitation and clay1, along with the interaction between AWDR and clay1 are correlated to ΔYield. Likewise, the evenness of total precipitation from the time of planting to the time of topdress (SDI) is significantly related to EONR. While not practical, other significant relationships may have been seen if weather information was considered following topdress.

Variability across a regional landscape makes relating specific soil and weather variables to ΔYield and EONR across sites and growing season's complex. Relationships found in this investigation could possibly be used to explain why N recommendation tools do not perform well when compared to EONR. If so, then these same relationships could be used to modify those tools to make them better performing. Since N loss off fields into rivers and streams is still considered a major environmental issue in modern agriculture (Roberts et al., 2010), more adaptive N recommendation tools that are better performing are needed to help farmers to produce economic optimal yields environmentally sound.

3.6 Bibliography

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3.7 Tables and Figures

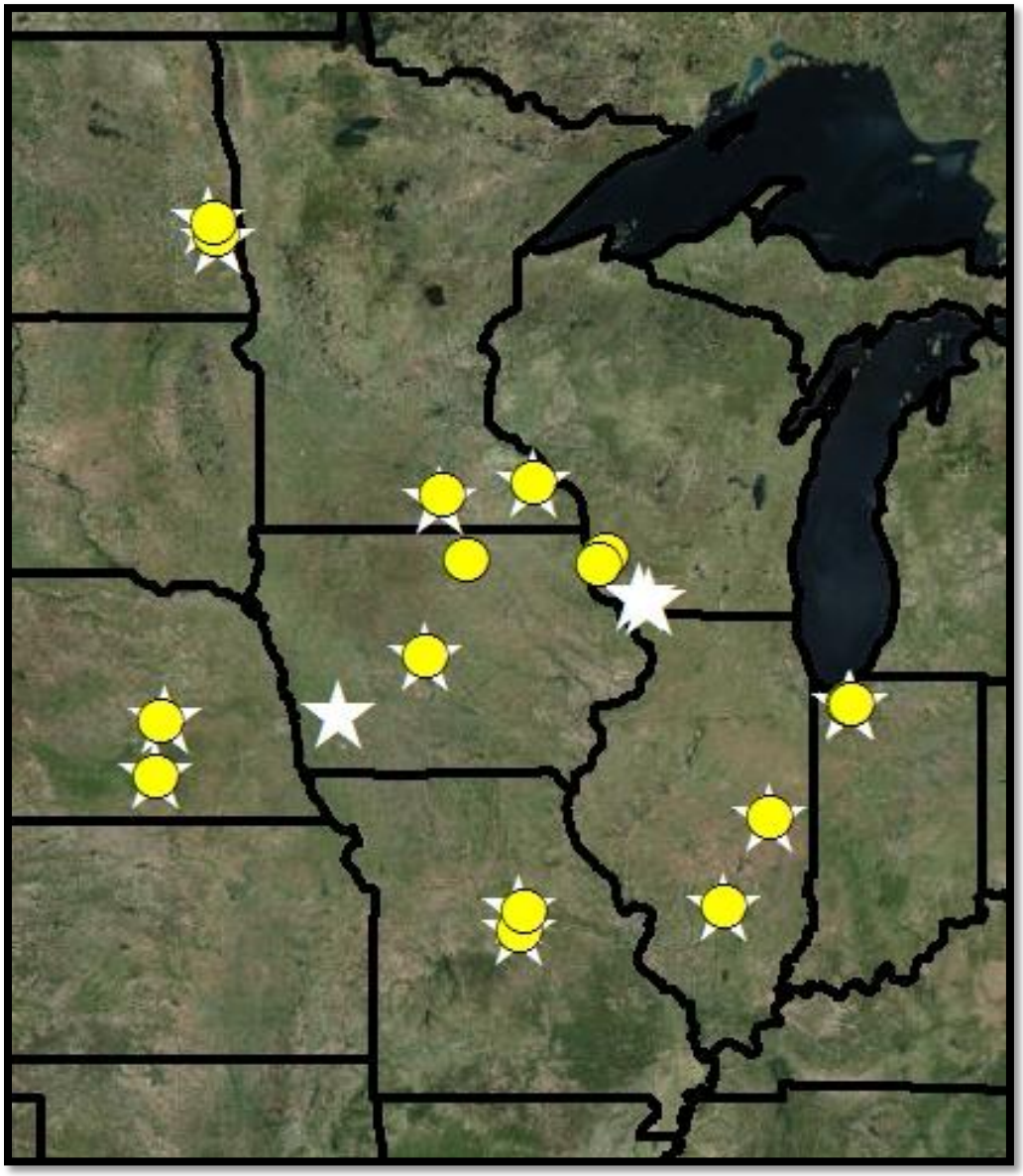

Figure 3.1. Field research sites were located within eight U.S. Corn Belt states (Iowa, Illinois, Indiana, Minnesota, Missouri, Nebraska, North Dakota, and Wisconsin). Each state contained two sites for two growing seasons (2014 - 2015), totaling 32 sites. The 2014 sites are represented by yellow circles while the 2015 sites are represented by white stars.

Table 3.1. Management description for the 16 sites for the 2014 growing-season. Each of the eight participating states chose two sites that contrasted in productivity within the state.

State	Site	Productivity	Previous Crop	Tiled	Irrigated	Tillage†	Hybrid	Seed Rate	Row Space	Planting Date	Topdress Date
								seeds/ha	cm		
IA	Ames	Low	SB	No	No	FC	P0987AMX	87,685	76	7 May	26 Jun
IA	Mason	High	SB	Yes	No	No-till	P0636AMX	86,450	76	9 May	9 Jul
IL	Brown1	Low	SB	No	No	FC	P1498AM	79,040	76	24 Apr	13 Jun
IL	Urbana1	High	SB	No	No	FC	P1498AM	86,450	76	25 Apr	15 Jun
IN	Loam1	High	SB	No	No	F chis/SP FC	P0987AMX	81,510	76	19 May	27 Jun
IN	Sand1	Low	SB	No	No	F chis/SP FC	P0987AMX	81,510	76	19 May	27 Jun
MN	New1	High	SB	Yes	No	-	P9917AMX	85,215	76	21 May	7 Jul
MN	Charles1	Low	SB	No	No	Vertical-till	P9917AMX	85,215	76	16 May	8 Jul
MO	Bay	Low	SB	No	No	FC	P1498AM	86,450	76	2 May	20 Jun
MO	Troth1	High	SB	No	No	No-till	P1498AM	86,450	76	2 May	21 Jun
ND	Amenia1	High	Corn	No	No	F chisel/ FC	P8954AM1	79,040	56	23 May	10 Jul
ND	Durbin1	Low	Corn	No	No	F chisel/FC	P8954AM1	79,040	56	23 May	10 Jul
NE	Brandes1	Low	SB	Yes	Yes	No-till	P1151HR	86,450	76	19 Apr	26 Jun
NE	SCAL1	High	SB	No	Yes	No-till	P1151HR	79,040	76	7 May	24 Jun
WI	Steuben	High	SB	No	No	No-till	P0636AMX	86,450	76	7 May	25 Jun
WI	Wauzeka	Low	SB	No	No	No-till	P0636AMX	79,781	76	6 May	25 Jun

†FC, field cultivated; F, fall; Chis, Chisel; SP, spring

Table 3.2. Management description for the 16 sites for the 2015 growing season. As done previously, each of the eight participating states chose two sites ranging in productivity of the 2015 growing season.

State	Site	Productivity	Previous Crop	Tiled	Irrigated	Tillage†	Hybrid	Seed Rate	Row Space	Plant Date	Topdress Date
								seeds/ha	cm		
IA	Boone	Low	SB	No	No	FC	P0987AMX	86,450	76	18 May	7 Jul
IA	Lewis	High	SB	No	No	FC	P1498AM	85,215	76	29 Apr	7 Jul
IL	Brown2	Low	SB	No	No	SP FC/ F deep ripped	P1498AM	86,450	76	28 Apr	16 Jun
IL	Urbana2	High	SB	No	No	FC / F deep ripped	P0987AMX	86,450	76	23 Apr	15 Jun
IN	Loam2	High	SB	No	No	FC	P0987AMX	80,275	76	29 Apr	17 Jun
IN	Sand2	Low	SB	No	No	No-till	P0987AMX	80,275	76	29 Apr	17 Jun
MN	New2	High	SB	No	No	F FC/ SP FC	P0157AMX	87,685	76	18 Apr	26 Jun
MN	Charles2	Low	SB	No	No	Vertical-till	P0157AMX	85,215	76	1 May	1 Jul
MO	Lonetree	Low	SB	No	No	FC	P1498AM	86,450	76	17 Apr	19 Jun
MO	Troth2	High	SB	No	No	FC	P1498AM	86,450	76	14 Apr	10 Jun
ND	Amenia2	High	Corn	Yes	No	No-till	P9188AMX	83,980	56	24 Apr	14 Jun
ND	Durbin2	Low	Corn	No	No	No-till	P9188AMX	83,980	56	24 Apr	18 Jun
NE	Brandes2	Low	SB	No	Yes	F chisel/ SP FC	P1151HR	86,450	76	19 Apr	29 Jun
NE	SCAL2	High	SB	No	Yes	F chisel/ SP FC	P1151HR	83,980	76	24 Apr	24 Jun
WI	Belmont	Low	SB	No	No	No-till	P0987AMX	90,155	76	4 May	1 Jul
WI	Darling	High	SB	No	No	No-till	P0987AMX	93,119	76	4 May	1 Jul

†FC, field cultivated; F, fall; Chis, Chisel; SP, spring

Table 3.3. Sixteen different N fertilizer rates split over two times were replicated four times at each site.

Trt #	Planting N	Topdress N	Total N
	——————kg ha^{-1}——————		
1	0	0	0
2	45	0	45
3	90	0	90
4	135	0	135
5	180	0	180
6	225	0	225
7	270	0	270
8	315	0	315
9	45	45	90
10	45	90	135
11	45	135	180
12	45	180	225
13	45	225	270
14	45	270	315
15	90	90	180
16	90	180	270

Table 3.4. The economic optimum N rate (EONR), corn yield response to N (ΔYield), surface (0-30 cm) soil organic matter (SOM), SSURGO surface (0-30 cm) clay content, precipitation (PPT), and abundant and well distributed rainfall (AWDR) for all 32 site locations. The amount of irrigation was included in both PPT and AWDR for sites with irrigation.

Year	State	Site	EONR	ΔYield	SOM	Clay	PPT	AWDR
			kg N ha^{-1}	Mg ha^{-1}	----g $100g^{-1}$----		------cm------	
2014	IA	Ames	155	6.3	2.4	21	25	16
	IA	Mason	153	7.2	3.2	23	33	22
	IL	Brown	237	8.4	1.1	15	22	15
	IL	Urbana	263	9.8	2.7	26	27	18
	IN	Loam	172	6.6	2.1	23	25	16
	IN	Sand	192	6.1	1.3	9	28	18
	MN	New	158	3.4	5.9	31	28	16
	MN	Charles	117	5.9	2.1	18	24	15
	MO	Bay	177	8.1	1.6	24	17	10
	MO	Troth	188	7.3	1.2	23	15	9
	ND	Amenia	164	6.5	3.1	20	14	9
	ND	Durbin	165	4.1	3.9	49	16	11
	NE	Brandes	205	7.6	1.2	7	28	18
	NE	SCAL	138	2.5	2.3	30	23	13
	WI	Steuben	77	4.4	2.2	23	22	13
	WI	Wauzeka	119	3.6	2.0	17	25	14
2015	IA	Boone	187	7.7	2.6	21	21	16
	IA	Lewis	107	5.5	2.3	31	25	11
	IL	Brown2	124	6.0	1.2	15	21	9
	IL	Urbana2	237	7.2	2.5	26	16	23
	IN	Loam2	160	5.3	2.4	23	33	10
	IN	Sand2	206	9.8	1.2	9	15	20
	MN	New2	151	4.8	4.4	30	32	15
	MN	Charles2	166	4.5	2.1	18	22	25
	MO	Lonetree	314	9.3	1.9	24	33	11
	MO	Troth2	314	7.1	1.8	28	17	14
	ND	Amenia2	155	6.2	1.9	15	22	8
	ND	Durbin2	139	5.3	4.6	49	13	13
	NE	Brandes2	198	7.8	0.9	6	20	13
	NE	SCAL2	27	0.9	2.6	30	41	24
	WI	Belmont	15	0.3	2.7	26	19	13
	WI	Darling	174	3.2	3.4	22	22	16

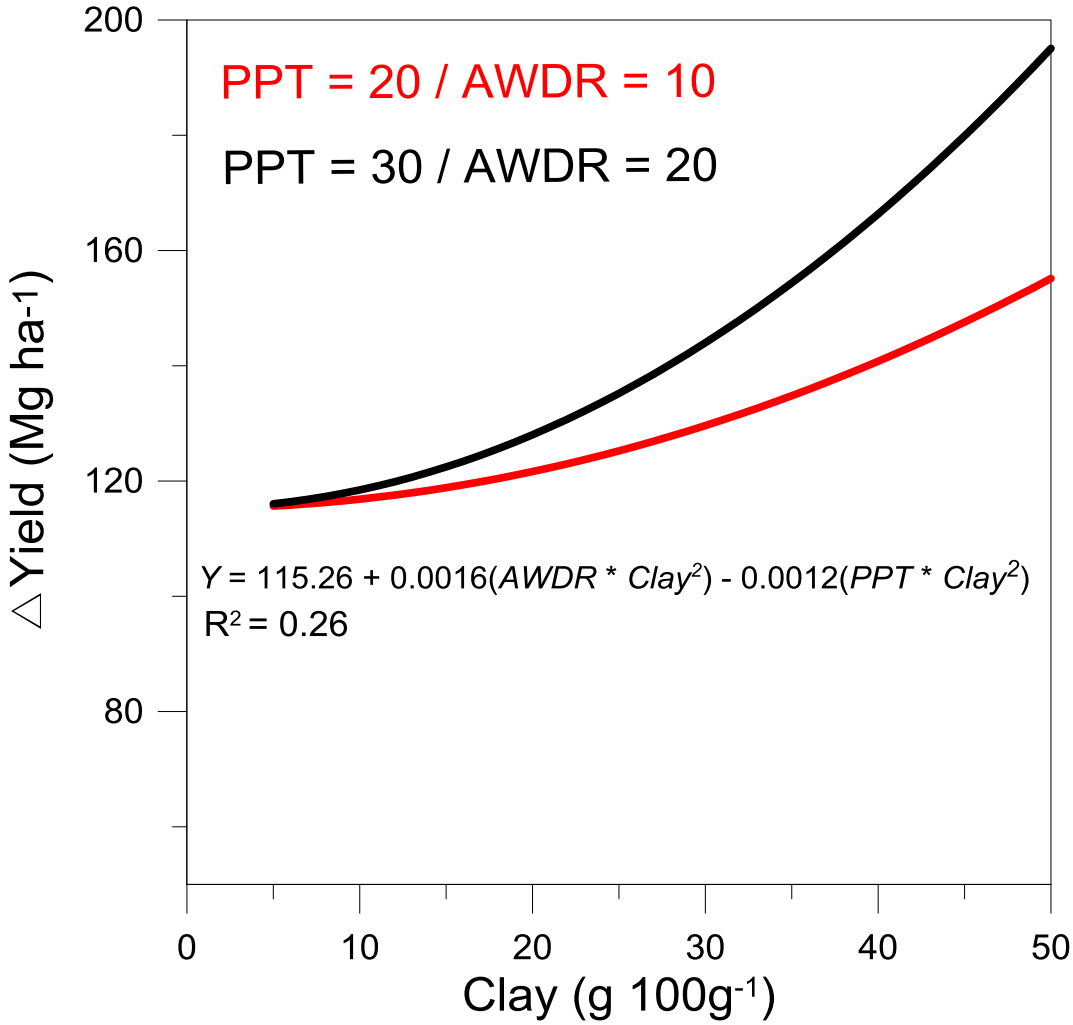

Figure 3.2. The relationship between SSURGO measured clay (0-30 cm) with abundant and well distributed rainfall (AWDR), precipitation (PPT) and corn N response (ΔYield), using the final model produced by the GLMSELECT function in SAS 9.2. Weather information collected from the time of planting to the time of topdress was used to calculate PPT (cm) and AWDR (cm). In general, as the amount of clay, PPT, and AWDR increase ΔYield increases. This supports previous claims (Tremblay et al., 2012) that as these variables increase, conditions ripen for N loss through denitrification resulting in increased responsiveness to N fertilizer application.

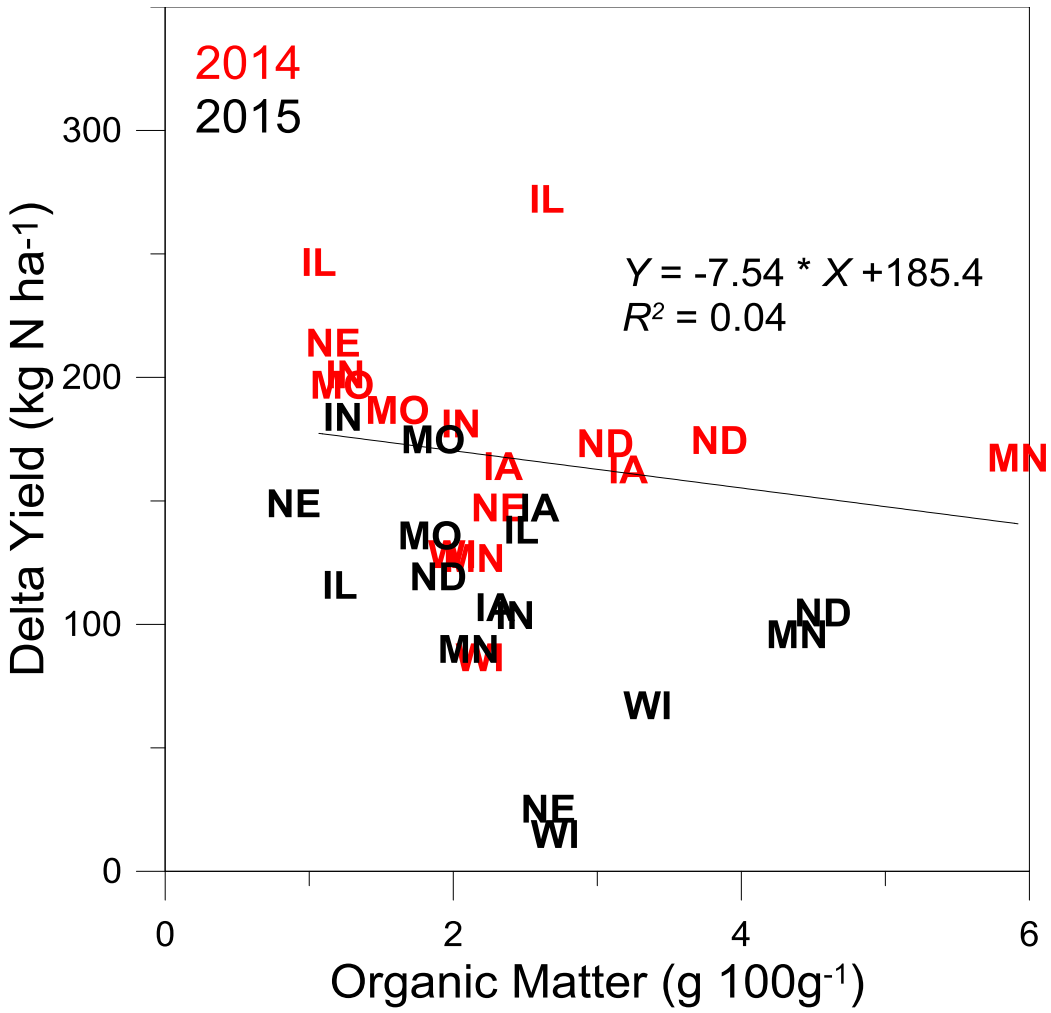

Figure 3.3. Delta yield (economic optimum N rate – grain yield with no N fertilizer applied) shown as a function of actual measured soil organic matter from 0 – 30 cm (SOM1) for 32 sites over two growing seasons (2014 – 2015). Even though significant, SOM1 is poorly related (r^2 =0.04). Generally, as SOM1 increases, the cation exchange capacity, soil aggregation, water infiltration and aeration increase (Sylvia et al., 2005). Larger amounts of SOM imply larger pools of plant available N lowering the responsiveness to added N fertilizer.

Table 3.5. Soil and weather variables found significant in relation to corn N response (ΔYield) across 32 site locations. The PPT, AWDR, and SDI were all calculated using weather information collected from the time of planting to the time of topdress. These significant linear and two-way linear variables from both SSURGO and Measured datasets were then used in a step-wise, cross-validation procedure to produce a final model. Variables included in the final model for each soil data source are presented.

	Significant Soil and/or Weather Varibles	**Before Cross-validation**		**Included in Final Model**
		p-value	*Adj.* R^2	
SSURGO	Clay	0.032	0.116	
	Clay X AWDR	0.036	0.110	
	Clay X PPT	0.011	0.169	
	Clay X PPT^2	0.037	0.108	
	$Clay^2$ X AWDR	0.022	0.135	Yes
	$Clay^2$ X PPT	0.011	0.172	Yes
	$Clay^2$ X PPT^2	0.013	0.162	
Measured	SOM	0.012	0.164	Yes
	SOM X GDD	0.020	0.141	
	SOM X AWDR	0.032	0.116	
	SOM X PPT	0.017	0.149	
	SOM X PPT^2	0.040	0.105	
	SOM X SDI	0.023	0.133	
	PAWC X PPT	0.041	0.103	
	Clay X PPT	0.047	0.096	

Table 3.6. Soil and weather variables found significant in relation to the economic optimum N rate (EONR). Precipitation and the SDI were calculated using weather information gathered from the time of planting to the time of topdress. Following the cross-validation, the SDI was the only remaining soil or weather variable significantly related to EONR.

	Significant Soil and/or Weather Variables	**Before Cross-validation**		**Included in Final Model**
		p-value	*Adj.* R^2	
Weather	SDI	0.041	0.103	Yes
SSURGO	$Clay^2$ X PPT^2	0.096	0.059	
Measured	PAWC	0.091	0.0511	

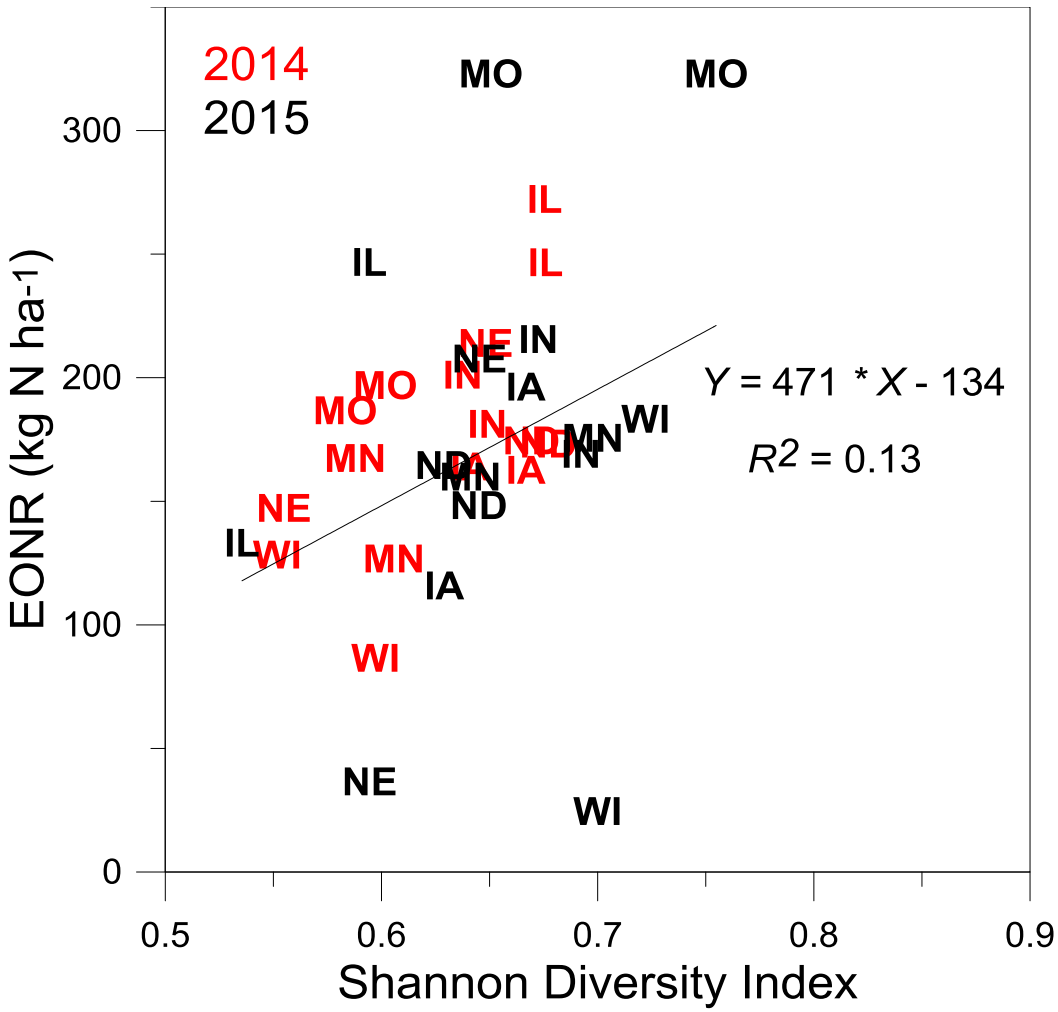

Figure 3.4. The Shannon Diversity Index (SDI) for 32 sites over two growing seasons (2014 – 2015) related to the economic optimum N rate (EONR). Weather values needed to calculate SDI were collected from the time of planting to the time of sensing. Generally, as the SDI value increased, implying a greater evenness of total rainfall, the EONR increased. This suggests frequent rainfall events preserve soil moisture, promote N loss through denitrification and leaching, as well as increase responsiveness to N fertilizer ultimately increasing the EONR.

Chapter 4: Modifying the University of Missouri Corn Canopy Sensor Algorithm Using Soil and Weather Information

4.1 Abstract

Corn production across the U.S. Corn belt can be often limited by the loss of nitrogen (N) due to leaching, volatilization and denitrification. The use of canopy sensors for making in-season N fertilizer applications has been proven effective in matching plant N requirements with periods of rapid N uptake (V7-V11), reducing the amount of N lost to these processes. However, N recommendation algorithms used in conjunction with canopy sensor measurements have not proven accurate in making N recommendations for many fields of the U.S. Corn Belt. Objectives for this research were to determine if soil and weather information could be used to make the University of Missouri canopy reflectance sensing algorithm more accurate. Nitrogen response trials were conducted across eight states over two growing seasons, totaling 32 sites (four per state) with soils ranging in productivity. Reflectance measurements at ±V9 were used with the University of Missouri canopy sensor algorithm to calculate an in-season N fertilizer recommendation. This recommendation was related to the economic optimal N rate (EONR). The University of Missouri algorithm was only mediocre in predicting EONR, averaging within 61 kg N ha^{-1} of EONR when target corn received no N at-planting and within 74 kg N ha^{-1} of EONR when target corn received 45 kg N ha^{-1} at-planting. However, when this algorithm was adjusted using weather and either measured or USDA SSURGO soil properties the suggested N fertilizer recommendation improved, coming within an average of 52 kg N ha^{-1} of EONR when the target corn

received no N at-planting. The error as determined by the root mean square error (RMSE), for corn receiving 45 kg N ha^{-1} at-planting the RMSE was 74 kg N ha^{-1} without soil and weather and 53 kg N ha^{-1} with the soil and weather adjustment. This suggests the incorporation of soil and weather information into other canopy sensor algorithms may enhance their accuracy at predicting site-specific EONR.

4.2 Introduction

Efficient nitrogen (N) management in corn (*Zea mays* L.) is critical for increasing grower profits and preventing environmental pollution. Fertilizer applications that match end-of-season measured economic optimum N fertilizer rate (EONR) can reduce N loss while protecting grower profits and the environment (Scharf et al., 2002; Roberts et al., 2010; Scharf et al., 2011). However, between- and within-field spatial variability of soil characteristics and variation in year-to-year weather factors make it difficult to determine the right amount of N fertilizer needed early in the season to match EONR.

Crop canopy reflectance sensors capture plant condition information (greenness and biomass) from small areas within fields and therefore can assess spatially-variable N requirements. Such a diagnostic tool therefore can aid in recommending the correct amount of N fertilizer applied to reach optimal yields (Scharf et al., 2002; Kitchen et al., 2010; Barker and Sawyer, 2010; Scharf et al., 2011). Unlike soil- or tissue-test based in-season N fertilizer recommendations, canopy sensors are directly mounted to a fertilizer applicator making it possible to collect reflectance data and apply variable N fertilizer in an on-the-go operation.

Canopy sensors emit visible and near infrared wavelengths of modulated light onto the corn canopy and measure the amount reflected back (Shanahan et al., 2003). The photosynthetic health of a corn plant can be determined by using the relative absorption of visible wavelengths of light, while the plant's structural size is primarily captured using near infrared wavelengths. Typically both types of wavelengths are measured by canopy sensors and some type of vegetative index is calculated (Kitchen et al., 2010). The index is directly related to the N health of the plant. Compared to chlorotic and deficient N plants, healthy green corn plants absorb more visible light, and as the plant gets larger they reflect more near infrared light. Also, the soil absorbs more near infrared light than plants providing an additional contrast in evaluating crop health. Thus, the application of reflectance canopy sensing for N management often is based upon the relative reflectance readings between adequately N fertilized corn and N deficient corn (Biggs et al., 2002; Kitchen et al., 2010). Reflectance data are first gathered from a strip or area in the field that is not N-limited. This is called an N reference strip and is usually established at planting by applying sufficient amounts of N fertilizer. Following the N-reference strip, reflectance data are then obtained from corn plants intended for fertilization (sometimes referred to as the 'target' corn). Using an N reference strip normalizes the reflectance data and sets a standard for defining the deficiency of 'target' corn. Gathered reflectance data are then used with an algorithm to produce an N fertilizer recommendation. These algorithms are considered to be at the core of successful canopy sensor based N fertilizer management (Scharf, 2010).

Canopy sensor algorithms are the mathematical expressions used to transform reflectance readings into an in-season N fertilizer recommendation. The unique growing conditions and environments these algorithms were developed for may limit their universal adoption. Utilizing different approaches for corn, many canopy sensor algorithms have been developed. The University of Missouri (MU) corn algorithm is one commonly used to transform canopy sensing information into a N fertilizer recommendation. It is a linear-based model requiring only the gathered canopy reflectance measurements. Variations have been made to accommodate early-, mid-, and late vegetative growth stages (Scharf et al., 2011).

Financial benefits have been documented by using the MU algorithm to synchronize the application of N fertilizer with corn N uptake. Fifty-five on-farm trials during 2004 to 2008 were conducted in Missouri where canopy sensing was used to inform topdress N fertilizer application rates (Scharf et al., 2011). Sensing N applications were then compared to a fixed rate that producers' used on these same fields. Across all fields, canopy sensors increased partial grower profits by an average of \$42 ha^{-1} over producer rates. In another assessment over three differing soil areas conducted from 2004 to 2007 canopy sensor N fertilizer rates performed better than producer chosen N fertilizer rates on about half of 16 field-scale experiments (Kitchen et al., 2010). On average they found using canopy sensing generated a \$25 to \$50 ha^{-1} profit. However, the MU algorithm's performance on a regional scale across the U.S. Cornbelt, seen in chapter two of this thesis, demonstrated a mediocre performance. The question considered here is, could the performance of the algorithm be improved by

incorporating into the algorithm soil or weather information, such as that discussed in chapter three?

Weather factors such as precipitation and temperature generally drive plant growth and influence soil conditions (Tremblay and Bélec, 2006), which ultimately influence corn yield. Monthly rainfall has been proven to effect corn yield variability (Teigen and Thompson, 1995). Corn was generally found to respond more to applied N fertilizer during years of above-average rainfall when compared to years of below-average rainfall (Yamoah et al., 1998). Additionally, N response across North America was found to be most affected by precipitation during June and July, as well as by temperatures during July and August (Jeutong et al., 2000). Some have identified the distribution or evenness of rainfall as being significant in describing responsiveness to N fertilizer, thus affecting yield (Shaw, 1964; Reeves et al., 1993; Tremblay et al., 2012). For example, frequent rainfall events were observed in 51 studies from 2006 to 2009 in several North American locations and were explained to have high soil moisture early in the growing season that promoted N loss through denitrification and leaching, as well as increased responsiveness to N fertilizer (Tremblay et al., 2012). Rainfall and temperature are generally accepted as metrics directly impacting yield-limiting soil factors of oxygen levels, biological activity, decomposition of organic matter to soil mineral N, nutrient availability, plant available water (PAWC), and ultimately crop yield (Power et al., 2001; Tremblay, 2004; Tremblay and Bélec, 2006; Kyveryga et al., 2007; Shanahan et al., 2008; Tremblay et al., 2012).

Spatially-diverse soil properties at sub-field to regional scales are key to understanding crop N needs. Soil texture, soil organic matter (SOM), and PAWC combined with varying total rainfall, the evenness of rainfall, and temperature, contribute to the complexities of N fate in crops and the environment (Power et al., 2001; Tremblay et al., 2004). Multiple N loss processes and pathways can exist in any given field. Significant denitrification (the conversion of NO_3^- to N0x and N_2 gases) most often occurs in clayey textured soils experiencing anaerobic soil conditions from excessive rainfall and with warm soil temperatures (Blevins et al., 1996). In contrast, NO_3^- leaching below the rooting depth results when high amounts of rainfall occur and is more pronounced on soils with low water holding capacity or coarse textured soils (Power et al., 2001). Volatilization, (the loss of N through ammonia-NH_3 gas), may also occur if certain N fertilizers, such as urea, are not incorporated into the soil (Ma et al., 2010). These weather-soil interactions result in varying field conditions, suggesting the need for targeting of N management to match these variations. Research is needed to decide if and how these soil and weather variables can improve N fertilizer recommendations to help match EONR.

Soil texture effects soil water flow, available N, PAWC, the transportation and availability of ions (Schaetzl and Anderson, 2014), and crop yield (Zhu et al., 2009; Armstrong et al., 2009; Tremblay et al., 2012). While conflicting results exist, corn yield is generally greater on coarse-textured soils during wet years than during dry years. Also, corn yields tend to be greater on fine-textured soils during dry years than during wet years (Tremblay et al., 2011). Fifty-seven studies on smallholder farms in sub-

Saharan Africa demonstrated the effect of soil texture on N fertilizer response. Nitrogen response was found to be greater on clay soils when compared to loam or sandy soils (Chivenge et al., 2011). Similarly, in North America, finer textured soils were found to respond more to N fertilizer (Tremblay et al., 2012). Soil organic matter has also proven to be related to corn yield; soil organic matter makes up a small percentage of the total soil volume (<5%) but has a large effect on other soil properties (Sylvia et al., 2005). As SOM increases, the cation exchange capacity increases, soil aggregation improves, water infiltration rates rise and aeration increases. Collectively, these effects ultimately improve growing conditions.

Soil information can be obtained from different sources. Through the USDA-NRCS Soil Survey Geographical database (SSURGO), the most used conventional soils database in the United States (Yang et al., 2011), most of the previously mentioned soil variables can be obtained. The accuracy and precision of SSURGO information is affected by mapping techniques, the level of spatial detail, and the exactitude of soil attributes (Zhu, 1997; Zhu et al., 2001). Efforts to verify SSURGO reports with actual soil measurements have given contradictory results. Field-truthing of SSURGO reports on the Hunewell ranch in Erath County, Texas showed poor relationships between SSURGO estimated soil texture and pH to actual samples (Zylman et al., 2015). Variation between SSURGO and the collected samples was greatest in erosional areas and transitional areas between SSURGO mapping units. However, research performed on forested soils in the northern Appalachian Plateau of Pennsylvania comparing horizon type, color, percentage of rock fragments, textural class, structure, and acidity between actual soil measurements and

the original NRCS report found 80% of the plots evaluated matched the original report. Differences found between field measurements and NRCS descriptions were attributed to dissimilarities in mapping models, changes in topography, field personnel, and the knowledge available to them at the time of the original description. Relative to how soil information might be used to quantify corn N response, research is needed that compares SSURGO descriptions of agricultural soils with actual field-measured soil properties (Drohan et al., 2003).

The objective of this research was to determine if soil and weather information could be used to inform the MU canopy sensor algorithm in making a better-performing in-season N fertilizer recommendation. Sub-objectives of this research were to compare algorithm performance with weather and soil information for 1) two different target N fertilizer rates; and 2) when employing SSURGO soil information versus actual within-field soil measurements.

4.3 Materials and Methods

4.3.1 Research Sites and Locations

This research was conducted as part of public-private collaboration between eight major land-grant universities (University of Iowa, University of Illinois, University of Indiana, University of Minnesota, University of Missouri, North Dakota State University, University of Nebraska, and the University of Wisconsin) within the US Corn Belt and DuPont Pioneer. This project is commonly referred to as the, “Performance and Refinement of Nitrogen Fertilization Tools” project. The approach for this research was

fundamental N fertilizer response field-plot studies conducted with standardized protocols and methods across a wide range of soil and weather conditions. Yield and soil measurements from these plot studies provided both the measurements needed as well as N response functions.

Thirty-two corn N response trials were conducted during 2014 to 2015 in eight Midwestern Corn Belt States. In each state, two sites ranging in productivity were selected for each growing season, giving four sites per state (Figure 4.1). Productivity was determined by historical yield and general soil productivity. Research sites were planted at a target population of 86,450 plants ha^{-1} using Pioneer hybrids (DuPont Pioneer, Johnstown, IA) found suitable for the selected sites within the region. Most research sites followed soybean, however four sites followed corn. The MN New site and the IA Mason site were tiled drained. NE sites were irrigated. All but three sites received at least some form of tillage. Planting dates ranged from April 19 – May 23 and topdress/sensing dates ranged from June 7 – July 10. Descriptions of management for all sites are presented in Tables 4.1 and 4.2.

4.3.2 Plots and Treatments

Plot dimensions were state and site dependent and were determined by the planting (planter width) and harvesting (combine width) equipment available, but minimal plot harvest area was 18.6 m^2. Average research area size per site was 0.4 ha. Sixteen different N rate treatments replicated four times (totaling 64 plots per site) were used in a randomized complete block design (Table 4.3). Nitrogen treatments were

obtained using dry-prilled NH_4NO_3-N fertilizer broadcast applied. The "at-planting" fertilizer was applied within 48 hours of initial planting while the topdress fertilizer was applied between the eighth and tenth leaf. Treatment one was the non-fertilized control. Treatments 2 to 8 received all N at-planting in 45 kg N ha^{-1} increments from 45 to 315 kg N ha^{-1}, while treatments 9 to 14 received 45 kg N ha^{-1} at-planting and the rest at topdress in 45 kg N ha^{-1} increments from 45 to 270 kg N ha^{-1}. Treatments 15 and 16 received 90 kg N ha^{-1} at-planting with the remaining N at topdress.

4.3.3 Canopy Sensing

Reflectance measurements were collected using the RapidSCAN CS-45 (RS) Handheld Crop Sensor (Holland Scientific, Lincoln, NE) just prior to topdress application (growth stage V8-V10 leaf stage). Manufacturer recommendations were followed during initial canopy sensor setup. The sensor was held approximately 60 cm above the row as the operator steadily walked approximately 4 kph alongside the row. Only plot rows used for yield measurements were sensed. While the RS uses three different wavelengths of light, red (670 nm, VIS), red edge (720 nm, RE), and near-infrared (780 nm, NIR), only VIS and NIR were utilized in calculating vegetative indices for the N recommendation algorithms tested in this study.

4.3.4 Algorithm

The MU algorithm tested was an equation developed for the V8-V10 growth stage (Scharf et al., 2011). The vegetative index used in this algorithm is the Inverse Simple Ratio (ISR) and is defined as:

$$ISR = \frac{VIS}{NIR} \quad [1]$$

where VIS = reflectance of the visible wavelength, and NIR= reflectance of the near infrared wavelength. Measurements were taken to obtain ISR values from both N reference corn ($ISR_{reference}$) and target corn (ISR_{target}). The N recommendation was then calculated as follows:

$$NRec_{MU} = \left(280\ kg\ N\ ha^{-1} \times \frac{ISR_{target}}{ISR_{reference}}\right) - 224\ kg\ ha^{-1} \quad [2]$$

where $NRec_{MU}$= the recommendation in kg ha^{-1}.

One complication was this recommendation algorithm was developed with the Holland Scientific's Crop Circle 210 (CC-210), an earlier sensor model than the RS used in this study. The CC-210 sensor employed slightly different reflectance wavelengths than the RS. Thus in order to test this algorithm, reflectance measurements gathered with the RS had to be converted to equivalent CC-210 measurements. Simultaneous measurements from these two sensors were taken on V8-V10 corn stands over several growing seasons (unpublished data) and found related in the following way:

$$ISR = 0.454 + \ln(ISR_{RS}) \times 0.125 \quad [3]$$

where ISR= Inverse Simple Ratio needed for the MU algorithm, and ISR_{RS} = Inverse Simple Ratio of the RS. Once RS values were transformed into equivalent CC-210 values, the recommendation could be determined using Eq. [2].

4.3.5 Reflectance Measurements for Recommendations

Nitrogen application treatments used to calculate an average site level N-rich reference were those that received 135, 180, and 225 kg N ha^{-1} at-planting (Treatments 4, 5, and 6 in Table 4.3; n=12). The exception was the Lonetree site where because of extreme early-season N loss, noted with a visual N deficiency the plots that received 315 kg N ha^{-1} at-planting were used as the N-rich reference. Nitrogen recommendations were calculated using two scenarios to represent the target corn to be fertilized at ~V9. One was the average of all experimental units fertilized at planting with 45 kg N ha^{-1} (n=28), and the other from unfertilized experimental units (0 kg N ha^{-1}; n=4). Canopy sensor reflectance data from both the target plots and N-rich reference plots were used to calculate the vegetative index specific to the MU algorithm.

4.3.6 Soil and Weather

Both within-field soil measurements and SSURGO data were gathered for all sites and years. Soil EC_a surveys were performed one to four weeks prior to planting using a Veris 3100 (Veris Technologies, Salina, KS). Sensing was performed on 4.5 m spacing travelling 5 kph across the plot area. Perpendicular passes were made through the plot area to aid in the creation of an interpolated map.

Soil Characterization was done by sampling two 1.2 m soil cores with a diameter of 4.76 cm from each of the four replications at each site using a Giddings Model #5-UV / MGSRPSUV (Giddings Machine Company, Windsor, CO). The location of both soil cores in each replication was determined using the soil EC_a survey map performed just prior to sampling, such that core sites represented the range of soil differences within a site as

observed by soil EC_a. Both drilled cores were laid side-by-side and characterized and separated by horizon. One core was used to calculate bulk density (BD) and soil moisture while the other was processed and sent to the University of Missouri Soil Health Assessment Center for additional soil property analyses. Analyses included the following properties: particle size determination through the pipette method, cation exchange capacity (CEC), total carbon, total organic carbon, total inorganic carbon, SOM, pH (salt and water), and BD. Amount of clay (i.e. %clay) was calculated by using the particle size determination (R. Burt and Soil Survey Staff, 2014; Nelson and Sommers, 1996). Plant Available Water Content was determined using the Saxton and Rawls formula (Saxton and Rawls, 2006). This equation uses measured sand and clay textural information along with SOM and BD to determine soil moisture at both the permanent wilting point and field capacity. The difference between the soil moisture at field capacity and permanent wilting point results in PAWC. Following this analysis, the four cores from each site were averaged together to obtain site-level data.

Soil organic matter, PAWC and clay content values collected from SSURGO and the University of Missouri's Soil Health Assessment Center were depth-weighted to three intervals; 0-30cm, 0-61cm, and 0-91cm.

Each site's weather data were collected using a HOBO U30 Automatic Weather Station (Onset Computer Corporation, Bourne, MA). Daily temperatures were used to calculate growing degree days (GDD) while daily precipitation (and irrigation), in conjunction with the Shannon Diversity Index (a measure of evenness; SDI) was used to

calculate a measurement called abundant and well-distributed rainfall (AWDR; Tremblay et al., 2012). These variables were calculated using the equations below:

$$GDD = \frac{T_{Max}+T_{Min}}{2} - T_{Base} \quad [4]$$

where T_{Max} = maximum daily temperature, T_{Min} = minimum daily temperature and T_{Base} = 10^0 C. All temperature values were measured in degrees Celsius (^{0} C).

$$SDI = \left[-\sum pi \frac{\ln(pi)}{\ln(n)}\right] \quad [5]$$

where pi = daily rainfall/total precipitation, n = number of days in the specified time period being used.

$$AWDR = SDI \times Total\ Precipitation \quad [6]$$

where precipitation and AWDR are measured in cm. Weather data used in the analysis were collected between the date of planting to the date of canopy sensing and topdress.

4.3.7 Evaluation and Statistics

Data were analyzed by site using SAS version 9.2 (SAS Institute Inc., Cary, NC). The EONR was calculated using a quadratic-plateau function since it has generally been found to be the best model in describing corn yield response to N (Scharf et al., 2005; Cerrato and Blackmer, 1990). Proc NLIN in SAS 9.2 was used to fit the data to the quadratic-plateau function. The EONR (kg N ha^{-1}) was calculated for all 32 site years using treatments 1, 2, and 9-14 (Table 4.3) as shown:

$$EONR = \frac{(-b-(ratio)}{(2c)} \quad [7]$$

where *b* and *c* = linear and quadratic response coefficients from the optimized quadratic function, and ratio = \$0.88 kg^{-1} N/\$0.03 kg^{-1} grain (i.e., N price/corn price). The EONR was set to not exceed the maximum N rate (315 kg N ha^{-1}).

Differences between the MU algorithm recommendations and EONR (MU_{Diff}) were calculated as follows:

$$MU_{Diff} = NRec_{MU} - EONR \quad [8]$$

where the MU_{Diff} is in kg N ha^{-1}.

Linear regression, was performed for all soil (at all three depth intervals) and weather variables, at two different at-planting (0 and 45 kg N ha^{-1}) N rates, using the Proc REG function in SAS 9.2, to determine which were significant ($p < 0.10$) and related to the MU_{Diff}. The interactions between these variables were also modeled using linear regression ($p < 0.10$). University of Missouri Algorithm Adjustment

A total of three adjusted MU algorithms, for each at-planting N rate, were created. One algorithm was adjusted with significant weather variables, another with significant SSURGO variables combined with weather, and the last with significant measured soil measurements combined with weather variables. Adjustments were made to each algorithm based on the intercept correction and coefficients produced by the Proc GLMSELECT ($p < 0.05$). This model is a “leave one out” approach to minimize model bias when a site is dissimilar from the rest.

4.4 Results and Discussion

Models for No N At-Planting

Using the procedures described above the following are the determined models used to adjust the MU algorithm.

$$MU_{Weather} = NRec_{MU} - 270 + 434 \times SDI \quad [9]$$

$$MU_{SRGO} = NRec_{MU} - 246 + 435 \times SDI - 0.0002 \times (Clay_{30} \times PPT) \quad [10]$$

$$MU_{Meas} = NRec_{MU} - 228 + 450 \times SDI - 0.0632 \times (GDD \times SOM_{60}) \quad [11]$$

where all adjusted MU algorithm N recommendations are in kg N ha^{-1}; SDI = the evenness of rainfall from the time of planting to the time of sensing, $Clay_{30}$ = SSURGO surface clay (0-30 cm), PPT = precipitation from planting to sensing, GDD = the growing degree days from planting to sensing, and SOM_{60} **=** measured soil organic matter (0-60 cm).

Models for 45 kg N ha^{-1} At-Planting

$$MU45_{Weather} = NRec_{MU} - 262 + 483 \times SDI \quad [12]$$

$$MU45_{SRGO} = NRec_{MU} - 156 + 336 \times SDI - 6 \times 10^{-7} \times (Clay_{30} \times PPT) \quad [13]$$

$$MU45_{Meas} = NRec_{MU} - 126 + 329 \times SDI - 0.007 \times (PPT \times PAWC_{60}) \quad [14]$$

where all adjusted algorithm N recommendations are in kg N ha^{-1}. The SDI = the evenness of rainfall from the time of planting to the time or sensing, and $Clay_{30}$ =

SSURGO surface clay (0-30 cm) and *PPT* = precipitation from planting to sensing. $PAWC_{60}$ = measured plant available water (0-60 cm).

4.4.1 Impact of Soil and Weather Information on the Algorithm

As seen in chapter two of this thesis, the MU algorithm was mediocre in matching N fertilizer recommendations with EONR across a regional landscape. However, after adjusting the MU algorithm with gathered soil and weather information, N fertilizer recommendations improved (Figure 4.4). Algorithm N fertilizer rate recommendations for 32 sites are shown relative to EONR in Table 4.6 and scatter plots (Figure 4.2). Points on or near the 1:1 diagonal line indicate the algorithm performed well for making an N rate recommendation. Points below the line represent an underestimated N recommendation and sites above the line represent an over-estimated N recommendation.

The distribution of rainfall (SDI) from the time of planting to the time of sensing was the only weather variable, without interacting with soil measurements, that was found to be significantly related to the difference between the MU algorithm recommendations and EONR (Table 4.5 and Table 4.6). This is likely because precipitation and the distribution of precipitation largely influence the availability of N and/or N losses early in the growing season. Too much precipitation can deprive microbial bacteria of oxygen forcing them to respire anaerobically, using NO_3^- as an oxygen source (denitrification). This process ultimately decreases the amount of N available for plant uptake, possibly leading to decreased corn yield (Blevins et al., 1996).

An example of this was the MO Lonetree site. This site experienced large amounts of rainfall (33 cm) that was distributed evenly (SDI = 0.75) (Tables 4.7 and 4.8). Therefore, as the MU algorithm was adjusted for the SDI, the N recommendation increased from 236 to 299 kg N ha^{-1} (target corn = 0 N at planting) and from 238 to 353 kg N ha^{-1} (target corn = 45 kg N ha^{-1} at planting). This modification resulted in an N fertilizer recommendation within 15 kg N ha^{-1} of EONR for target corn that received no N at planting and an N fertilizer recommendation within 38 kg N ha^{-1} of EONR for target corn that received 45 kg N ha^{-1}.

The interaction between SSURGO surface clay (0-30 cm) and precipitation (for both corn target N rates) was also related to the differences between the algorithms recommendations and EONR. Soil texture, to some extent, determines the diffusivity, tortuosity, and permeability of water in the soil. Clayey soils have more surface area than medium or coarse textured soils, are mostly negatively charged, and are highly attracted to water (Schaetzl and Anderson, 2014), creating conditions that decrease PAWC and promote the loss of N through denitrification, which can shrink corn yield (Blevins et al., 1996). Also, soils with large clay percentages close to the surface of the soil are prone to large amounts of surface runoff due to slow infiltration rates (Schaetzl and Anderson, 2005). Nitrogen loss can also occur in the absence of clay through leaching, as seen on the Brandes and Brandes2 sites. These sites have <10% clay but received substantial amounts of water, likely resulting in leached NO_3^- (Table 4.8). Following the addition of SSURGO collected surface clay and it's interaction with precipitation, the MU algorithm recommendations improved for these sites.

Recommendations, for both target corn N rates and growing seasons, increased by as much as 69 kg N ha^{-1} resulting in an N fertilizer recommendation within 11 kg N ha^{-1} of EONR (Table 4.4).

Normally, as GDD increases, plant available N increases (Kay et al., 2006). Also, some have shown that thermal units, such as GDD, affect soil mineral N and ultimately response to N (Tremblay, 2004; Tremblay and Belec, 2006; Shanahan et al., 2008). These relationships may explain why the interaction between GDD and measured SOM (0-60 cm) was found related to the differences between the MU algorithm N recommendations and EONR (when using the no N at-planting corn target rate). Temperature is a common factor that controls the metabolic activity of certain types of bacteria that fix or transform N. If soil temperatures are ideal and sufficient amounts of mineralizable N exist, growing conditions and plant available N improve, likely also improving corn yield (Sylvia et al., 2005). However, if temperatures are not ideal or SOM levels are insufficient, lesser amounts of soil N are available for plant uptake followed by decreased yields. Including the interaction between GDD and measured SOM improved several site recommendations (when target corn N rate = no N at planting). With this modification, the MU algorithm recommendation for the Brown site increased by 53 kg N ha^{-1}, resulting in a rate only 27 kg N ha^{-1} below EONR. Likewise, with the modification the MU algorithm recommendation for the Sand2 site increased by 59 kg N ha^{-1} and resulted in a recommendation rate within 4 kg N ha^{-1} of EONR. Both sites had <1% SOM and an average amount of GDD (Table 4.8).

The interaction between precipitation and measured PAWC (0-60 cm) was also found significant (when using the 45 kg N ha^{-1} corn target rates) in describing the difference between the MU algorithms and EONR. Explanations for this are numerous. Water, as mentioned above, drives both soil and plant processes that are crucial for plant development and yield. These processes include and are not limited to photosynthesis, evapotranspiration, the movement of N to plant roots, N loss through leaching and denitrification, bacterial N fixation, and microbial respiration, all of which contribute to the fate of N and corn yield. All interactions found significant had a temporal component supporting observations from previous research that temporal variability driven by weather may be as or more important than spatial soil variability (Kitchen et al., 2005). Examples of improved site N fertilizer recommendations after incorporating the interaction between precipitation and measured PAWC into the MU algorithm are seen in the Mason, Sand2, and Darling sites. The Mason site recommendation increased by 26 kg N ha^{-1} to match EONR. The Sand2 site N fertilizer recommendation increased by 85 kg N ha^{-1} to be within 7 kg N ha^{-1} of EONR. An 87 kg N ha^{-1} increase for the Darling site resulted in an N application recommendation within 11 kg N ha^{-1} of EONR.

4.4.2 Weather versus Soil

When comparing the weather adjusted MU algorithm with the SSURGO and measured adjusted MU algorithms, considering both growing seasons and across both corn target N rates, the MU algorithm adjusted with measured soil information performed best (Figure 4.3; Table 4.9). When adjusted with measured soil information,

using the 45 kg N ha^{-1} corn target rate, the median value decreased from -41 kg N ha^{-1} to 0.3 kg N ha^{-1} (Figure 4.3). This produced an improvement in algorithm accuracy. The RMSE improved from 74 kg N ha^{-1} to 53 kg N ha^{-1} suggesting a meaningful improvement in precision. To a lesser extent, N recommendation accuracy and precision also improved with the weather adjusted MU algorithm and the SSURGO adjusted algorithm. These improvements are illustrated in Figures 4.4, 4.5, and 4.6 showing that a larger percentage of the 32 sites were within 30 kg N ha^{-1} of EONR than the unadjusted MU algorithm. Combining growing seasons, the percentage of sites within 30 kg N ha^{-1} of EONR improved from 34 to 53% when the algorithm was adjusted with weather and measured soil properties and the target corn received no N at-planting. When target corn received 45 kg N ha^{-1}, and combining growing seasons, the percentage of sites within 30 kg N ha^{-1} of EONR improved from 31 to 56% when the algorithm was adjusted with weather and measured soil variables. However, some differences between EONR and the MU algorithm recommendation were simply not explained by the weather and soil variables used here. Both the Belmont and Troth2 sites were largely unaffected by the modified MU algorithm. The Troth2 site had large amounts of standing water on the field caused by groundwater seep partially due to its proximity to the Missouri river and heavy rainfall events that occurred upriver. The Belmont site is historically known for being unresponsive to N (personal communication) for reasons unknown. Exploring other soil or weather factors may, in the future, help explain these responses.

4.4.3 The Effect of At-Planting Target Corn N Rate

Combining years, algorithm, unadjusted and adjusted, recommendations were generally higher and better performing when target corn received no N at planting versus corn fertilized with 45 kg N ha^{-1} at planting. Median, mean, and RMSE values all lowered when the target corn received no N at-planting (except for the median value of the MU algorithm that was adjusted with weather and measured soil variables) (Table 4.9). This shift would be expected since a crop unfertilized at planting would by the V9 growth stage show more N deficiency, and is evidence of the responsiveness of the sensor and algorithm to reflectance properties of the corn canopy. While this may be true, the likelihood of widespread adoption of applying no N at planting is minimal. These observations support the recommendation that canopy sensors should be reserved for areas where N stress is considered the most limiting plant growth factor (Barker and Sawyer, 2010; Solie et al., 2012).

4.4.4 Differences between Growing Seasons

The decline in accuracy seen in the unadjusted MU algorithm for the 2015 growing season (Figures 4.2, 4.3, and 4.5) may be attributed to abnormal excessive precipitation, particularly for the southernmost sites. At several sites, precipitation before and following sensing was excessive and frequent (Table 4.7). The 2015 Troth2 site received 28 cm of rain between sensing to plant maturity which is three times as much as the 2014 Troth site. Similarly, the 2015 Lonetree site, located on a claypan soil, received twice as much precipitation as the claypan soil 2014 Bay site. Excessive precipitation on claypan soil creates an environment for both significant surface runoff and

denitrification (Blevins et al., 1996). Nitrogen loss prior-to-sensing may be captured and corrected by the canopy sensor, but post-sensing N loss cannot be corrected without additional late season N applications. These excessive rainfall scenarios generally resulted in inaccurate N fertilizer recommendations. Also, the N recommendations given by the algorithms were highly sensitive to the difference in reflectance readings between the target and N-reference corn. Larger differences generally resulted in N fertilizer recommendations closer to EONR.

Following the adjustments for the 2015 growing season, median values were similar to those from the 2014 growing season (Figure 4.3), and the percentage of sites that adjusted to within 30 kg N ha^{-1}, in some instances, surpassed those from 2014 (Figures 4.4 and 4.5). However, while the accuracy may have increased, higher mean and RMSE values (Table 4.9) showed a decrease in precision compared to 2014. Definite improvements in both accuracy and precision were seen when soil and weather information was used to inform the MU algorithm for both growing seasons.

4.5 Conclusion

Singly and when combining growing seasons, all adjusted algorithms outperformed the original MU algorithm, at both target corn N fertilizer rates. Thus, even though canopy sensing uses the corn plant as a bioassay to generally capture the N health of the crop, health that is impacted by early-season soil and weather interactions, it was shown that additional direct soil and weather measurements could be used to improve the MU algorithm for sensor-based corn N recommendations.

The difference in performance between target N applications may be attributed to the ability of the canopy sensor to detect an N deficiency in the corn crop at the time of sensing. If, at the time of sensing, the target corn does not show any signs of N stress resulting in similar greenness and biomass between the target crop and N-reference crop, then the algorithm minimal recommended rate needs to be adjusted. The soil and weather modification could be considered as that adjustment. Differences in algorithm performances between growing seasons are attributed to the amount of precipitation from the time of sensing to the time of plant maturity. Most recommendations by the MU algorithm adjusted with measured soil data out performed those by the SSURGO adjusted algorithm; however SSURGO soil variables are easier and less expensive to collect. The increased performance by the measured soil variables may not be worth the added time and money it takes to collect samples.

Other soil and weather variables not mentioned or explored with this research may also be considered for modifying the MU algorithm for improved N fertilizer recommendations. Further, this same approach should be tried with other corn canopy sensor algorithms. Significantly, this work demonstrated that using soil and weather information improved the MU algorithm recommendation. The application of this work ultimately could lead to increased grower profit and lower negative environmental impacts.

4.6 Bibliography

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4.7 Tables and Figures

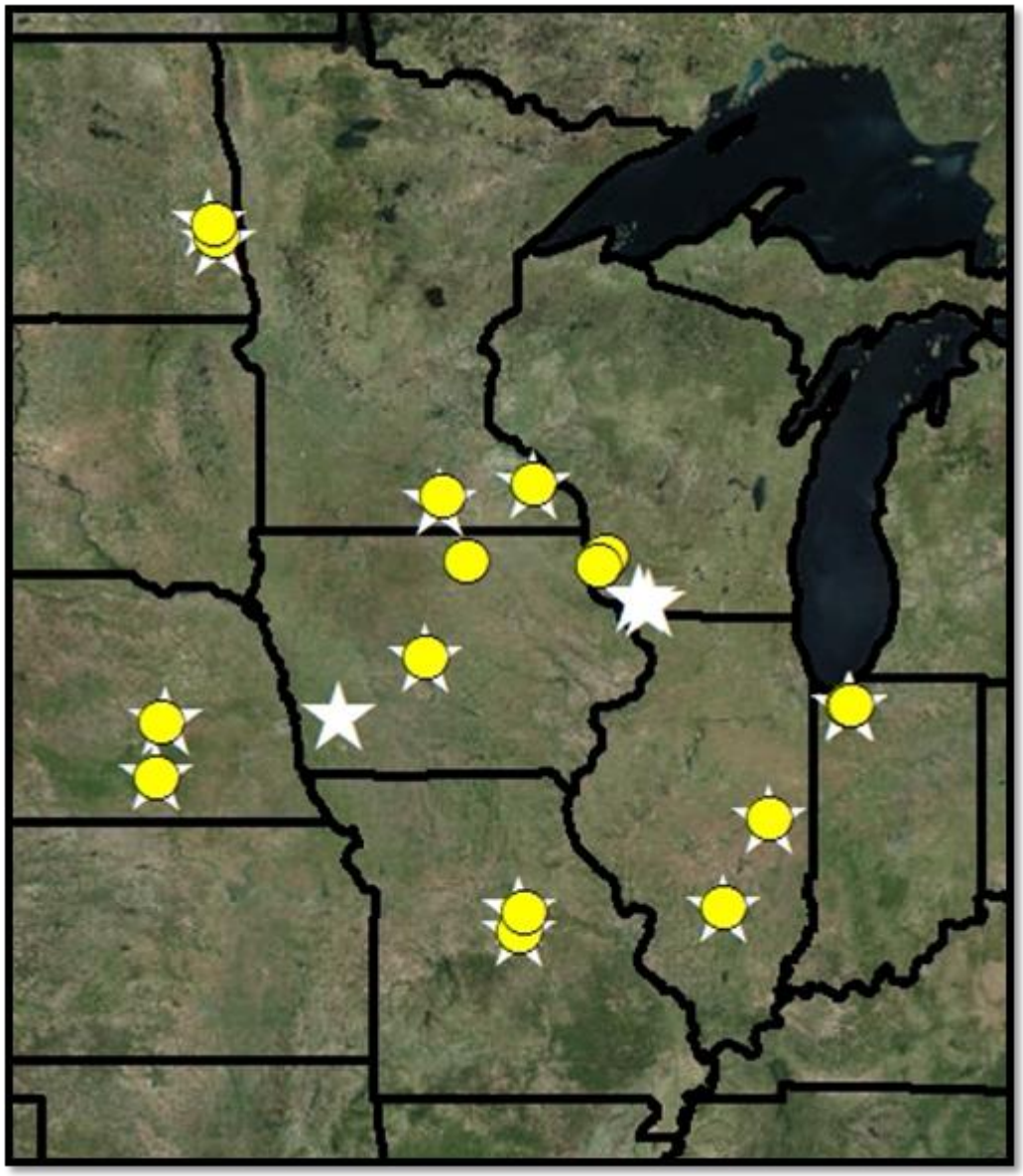

Figure 4.1. Field research sites were located within eight U.S. Corn Belt states (Iowa, Illinois, Indiana, Minnesota, Missouri, Nebraska, North Dakota, and Wisconsin). Each state contained two sites for two growing seasons (2014 - 2015), totaling 32 sites. The 2014 sites are represented by yellow circles while the 2015 sites are represented by white stars.

Table 4.1. Management description for the 16 sites for the 2014 growing-season. Each of the eight participating states chose two sites that contrasted in productivity within the state.

State	Site	Productivity	Previous Crop	Tiled	Irrigated	Tillage†	Hybrid	Seed Rate	Row Space	Planting Date	Sensing Date	Sensing Growth Stage
								seeds/ha	cm			
IA	Ames	Low	SB	No	No	FC	P0987AMX	87,685	76	7 May	26 Jun	V9
IA	Mason	High	SB	Yes	No	No-till	P0636AMX	86,450	76	9 May	9 Jul	V9
IL	Brown1	Low	SB	No	No	FC	P1498AM	79,040	76	24 Apr	13 Jun	V8
IL	Urbana1	High	SB	No	No	FC	P1498AM	86,450	76	25 Apr	15 Jun	V8.5
IN	Loam1	High	SB	No	No	F chis/SP FC	P0987AMX	81,510	76	19 May	27 Jun	V9
IN	Sand1	Low	SB	No	No	F chis/SP FC	P0987AMX	81,510	76	19 May	27 Jun	V9
MN	New1	High	SB	Yes	No	-	P9917AMX	85,215	76	21 May	7 Jul	V9
MN	Charles1	Low	SB	No	No	Vertical-till	P9917AMX	85,215	76	16 May	8 Jul	V10
MO	Bay	Low	SB	No	No	FC	P1498AM	86,450	76	2 May	20 Jun	V10
MO	Troth1	High	SB	No	No	No-till	P1498AM	86,450	76	2 May	21 Jun	V10.5
ND	Amenia1	High	Corn	No	No	F chisel/ FC	P8954AM1	79,040	56	23 May	10 Jul	V8.5
ND	Durbin1	Low	Corn	No	No	F chisel/FC	P8954AM1	79,040	56	23 May	10 Jul	V8.5
NE	Brandes1	Low	SB	Yes	Yes	No-till	P1151HR	86,450	76	19 Apr	26 Jun	V9
NE	SCAL1	High	SB	No	Yes	No-till	P1151HR	79,040	76	7 May	24 Jun	V8.5
WI	Steuben	High	SB	No	No	No-till	P0636AMX	86,450	76	7 May	25 Jun	V9
WI	Wauzeka	Low	SB	No	No	No-till	P0636AMX	79,781	76	6 May	25 Jun	V9

†FC, field cultivated; F, fall; Chis, Chisel; SP, spring.

Table 4.2. Management description for the 16 sites for the 2015 growing season. As done previously, each of the eight participating states chose two sites ranging in productivity of the 2015 growing season.

State	Site	Productivity	Previous Crop	Tiled	Irrigated	Tillage†	Hybrid	Seed Rate	Row Space	Plant Date	Sensing Date	Sensing Growth Stage
								seeds/ha	cm			
IA	Boone	Low	SB	No	No	FC	P0987AMX	86,450	76	18 May	7 Jul	V10
IA	Lewis	High	SB	No	No	FC	P1498AM	85,215	76	29 Apr	7 Jul	V10
IL	Brown2	Low	SB	No	No	SP FC/ F deep ripped	P1498AM	86,450	76	28 Apr	16 Jun	V9
IL	Urbana2	High	SB	No	No	FC / F deep ripped	P0987AMX	86,450	76	23 Apr	15 Jun	V9
IN	Loam2	High	SB	No	No	FC	P0987AMX	80,275	76	29 Apr	17 Jun	V10
IN	Sand2	Low	SB	No	No	No-till	P0987AMX	80,275	76	29 Apr	17 Jun	V10
MN	New2	High	SB	No	No	F FC/ SP FC	P0157AMX	87,685	76	18 Apr	26 Jun	V8
MN	Charles2	Low	SB	No	No	Vertical-till	P0157AMX	85,215	76	1 May	1 Jul	V9
MO	Lonetree	Low	SB	No	No	FC	P1498AM	86,450	76	17 Apr	19 Jun	V9
MO	Troth2	High	SB	No	No	FC	P1498AM	86,450	76	14 Apr	10 Jun	V9
ND	Amenia2	High	Corn	Yes	No	No-till	P9188AMX	83,980	56	24 Apr	14 Jun	V5
ND	Durbin2	Low	Corn	No	No	No-till	P9188AMX	83,980	56	24 Apr	18 Jun	V6
NE	Brandes2	Low	SB	No	Yes	F chisel/ SP FC	P1151HR	86,450	76	19 Apr	29 Jun	V9
NE	SCAL2	High	SB	No	Yes	F chisel/ SP FC	P1151HR	83,980	76	24 Apr	24 Jun	V8
WI	Belmont	Low	SB	No	No	No-till	P0987AMX	90,155	76	4 May	1 Jul	V9
WI	Darling	High	SB	No	No	No-till	P0987AMX	93,119	76	4 May	1 Jul	V9

†FC, field cultivated; F, fall; Chis, Chisel; SP, spring.

Table 4.3. Sixteen different N fertilizer rates split over two times were replicated four times at each site.

Trt #	Planting N	Topdress N	Total N
	——————kg ha^{-1}——————		
1	0	0	0
2	45	0	45
3	90	0	90
4	135	0	135
5	180	0	180
6	225	0	225
7	270	0	270
8	315	0	315
9	45	45	90
10	45	90	135
11	45	135	180
12	45	180	225
13	45	225	270
14	45	270	315
15	90	90	180
16	90	180	270

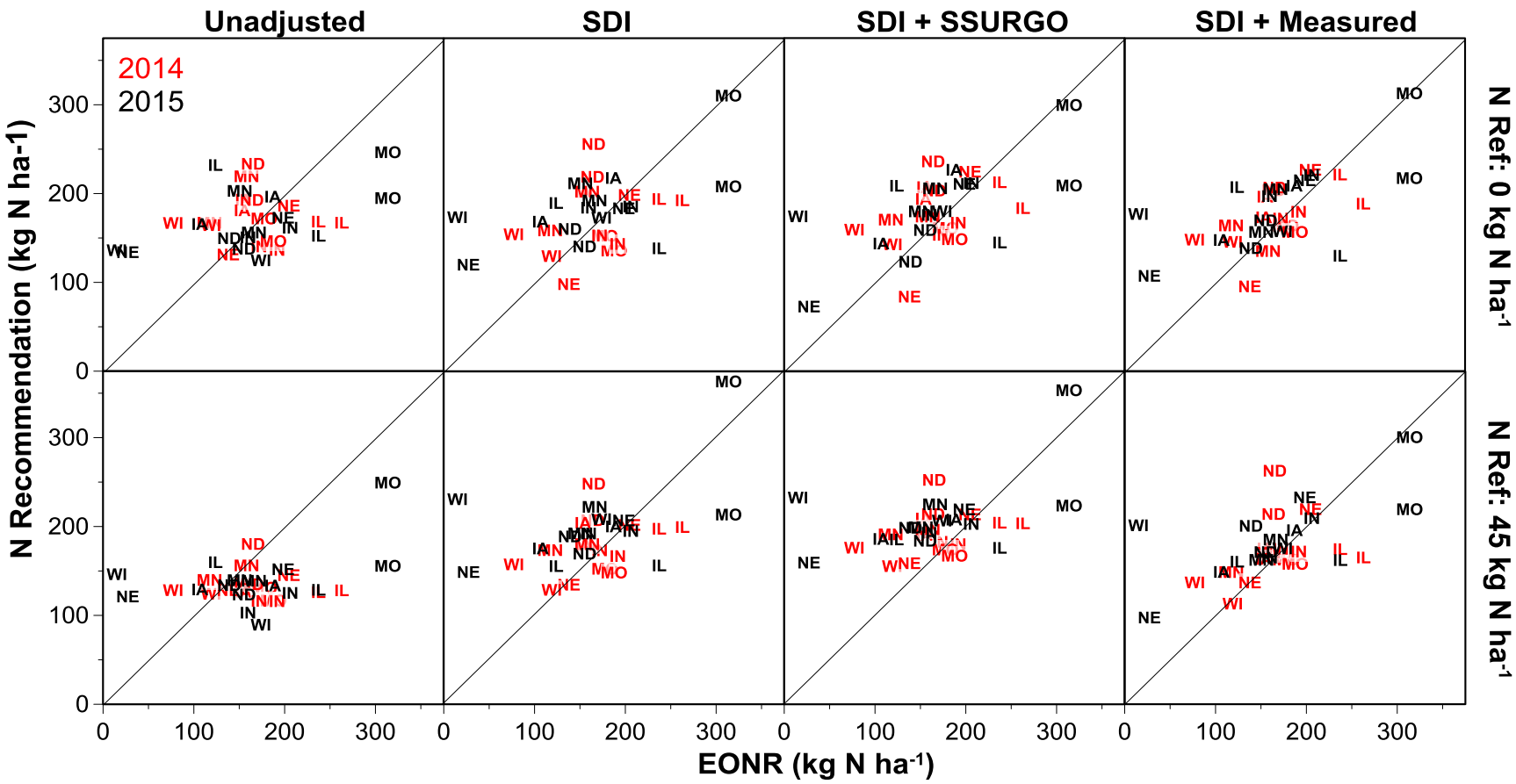

Figure 4.2. The unadjusted MU algorithm compared to the MU adjusted algorithms for both target corn N rates, for all 32 site locations across the 2014 and 2015 growing seasons. The diagonal line on each graph represents a 1:1 relationship between the economic optimum N rate (EONR) and the algorithms' recommendation. Ideally all sites would be on or close to this line suggesting the algorithm matched EONR. Sites below the line represent an underestimated N recommendation and sites above the line represent an over-estimated N recommendation. Recommendations were generally higher and better performing when target corn received no N at planting verses corn fertilized with 45 kg N ha^{-1} at planting. Generally across growing seasons and target corn N rates, soil or weather information used to modify the original MU algorithm improved performance. The 2014 sites are closer to the 1:1 line than 2015 sites which may be due to more variable weather experienced during the 2015 growing season.

Table 4.4. The economic optimum N rate and algorithm recommendations for 32 sites.

				0 N ha^{-1}				45 N ha^{-1}			
Year	**State**	**Site**	**EONR**	**Unadj**	**SDI**	**SDI+ SSURGO**	**SDI+ Measured**	**Unadj**	**SDI**	**SDI+ SSURGO**	**SDI+ Measured**
			kg N ha^{-1}								
2014	IA	Ames	155	182	191	196	185	116	168	180	164
	IA	Mason	153	170	191	182	162	127	193	198	153
	IL	Brown	237	157	183	202	210	115	187	194	164
	IL	Urbana	263	156	181	172	177	117	189	193	154
	IN	Loam	172	129	142	142	161	105	162	172	164
	IN	Sand	192	125	132	156	168	105	156	169	161
	MN	New	158	208	191	163	124	145	169	186	160
	MN	Charles	117	156	148	159	153	129	163	180	138
	MO	Bay	177	161	141	150	153	120	142	163	152
	MO	Troth	188	135	125	137	146	106	137	156	147
	ND	Amenia	164	182	208	225	193	124	196	203	203
	ND	Durbin	165	223	245	192	196	169	237	242	252
	NE	Brandes	205	175	187	213	216	134	191	203	209
	NE	SCAL	138	120	87	73	84	117	124	148	126
	WI	Steuben	77	156	143	148	137	117	147	165	126
	WI	Wauzeka	119	153	119	132	135	113	118	145	102
2015	IA	Boone	187	186	207	216	198	123	189	197	185
	IA	Lewis	107	155	157	133	137	118	165	175	138
	IL	Brown2	124	221	178	198	196	149	145	175	150
	IL	Urbana2	237	141	127	134	119	118	145	165	151
	IN	Loam2	160	140	173	165	186	92	181	182	154
	IN	Sand2	206	151	174	201	210	114	184	192	199
	MN	New2	151	192	201	169	146	129	181	188	152
	MN	Charles2	166	145	181	195	194	128	211	214	175
	MO	Lonetree	314	236	299	289	302	238	353	343	290
	MO	Troth2	314	184	197	198	206	145	203	213	209
	ND	Amenia2	155	127	129	148	159	112	159	173	160
	ND	Durbin2	139	139	149	112	127	123	178	188	190
	NE	Brandes2	198	162	172	200	204	140	196	209	222
	NE	SCAL2	27	123	109	62	96	110	138	149	87
	WI	Belmont	15	125	162	163	166	135	220	222	191
	WI	Darling	174	114	162	169	146	78	198	196	165

Table 4.5. Significant soil (within-field measured and SSURGO) and weather variables across 32 sites when using the no N at-planting corn target rate.

	Significant Soil and/or Weather Variables	**Before Cross-validation**		**Included in Final Model**
		p-value	*Adj.* R^2	
Weather	SDI	0.041	0.103	Yes
Within-field	SOM (0-30 cm)	0.056	0.088	
	GDD X SOM (0-30 cm)	0.042	0.102	
	GDD X SOM (0-60 cm)	0.030	0.123	Yes
	GDD X SOM (0-90 cm)	0.028	0.121	
	PPT X SOM (0-30 cm)	0.051	0.093	
	PPT X SOM (0-60 cm)	0.034	0.112	
	PPT X SOM (0-90 cm)	0.029	0.121	
	PPT^2 X SOM (0-30 cm)	0.079	0.070	
	PPT^2 X SOM (0-60 cm)	0.068	0.081	
	PPT^2 X SOM (0-90 cm)	0.057	0.086	
	SDI X SOM (0-60 cm)	0.088	0.064	
	SDI X SOM (0-90 cm)	0.094	0.061	
SSURGO	GDD X SOM (0-30 cm)	0.087	0.049	
	PPT X Clay (0-30 cm)	0.079	0.069	
	PPT X $Clay^2$ (0-30 cm)	0.060	0.083	Yes
	PPT X PAWC (0-60 cm)	0.088	0.052	
	PPT X SOM (0-90 cm)	0.096	0.059	
	PPT^2 X $Clay^2$ (0-30 cm)	0.057	0.086	

Table 4.6. Significant soil (within-field measured and SSURGO) and weather variables across 32 sites when 45 kg N ha^{-1} was used as the target corn N rate.

	Significant Soil and/or Weather Variables	**Before Cross-validation**		**Included in Final Model**
		p-value	*Adj.* R^2	
Weather	SDI	0.088	0.064	Yes
Within-field	PAWC (0-30 cm)	0.010	0.057	
	PAWC (0-60 cm)	0.086	0.065	
	GDD X SOM (0-60 cm)	0.030	0.057	
	GDD X SOM (0-90 cm)	0.028	0.058	
	PPT X Clay (0-90 cm)	0.093	0.061	
	PPT X PAWC (0-30 cm)	0.064	0.080	
	PPT X PAWC (0-60 cm)	0.054	0.089	Yes
	PPT X PAWC (0-90 cm)	0.057	0.087	
	PPT X SOM (0-60 cm)	0.034	0.085	
	PPT X SOM (0-90 cm)	0.029	0.073	
	PPT^2 X $Clay^2$ (0-90 cm)	0.099	0.051	
	PPT^2 X PAWC (0-30 cm)	0.095	0.060	
	PPT^2 X PAWC (0-60 cm)	0.091	0.062	
	PPT^2 X PAWC (0-90 cm)	0.086	0.065	
	PPT^2 X SOM (0-90 cm)	0.057	0.058	
SSURGO	AWDR X $Clay^2$ (0-30 cm)	0.085	0.044	
	PPT X Clay (0-30 cm)	0.064	0.080	
	PPT X $Clay^2$ (0-30 cm)	0.052	0.090	
	PPT^2 X Clay (0-30 cm)	0.091	0.062	
	PPT^2 X $Clay^2$ (0-30 cm)	0.044	0.099	Yes

Table 4.7. The amount of precipitation before and after topdress for all 32 site locations

Year	State	Site	Precipitation from Planting to Topdress	Precipitation from Topdress to Plant Maturity
			———————cm	———————
2014	IA	Ames	25	49
	IA	Mason	33	14
	IL	Brown	22	33
	IL	Urbana	27	40
	IN	Loam	25	39
	IN	Sand	28	20
	MN	New	28	18
	MN	Charles	24	6
	MO	Bay	17	17
	MO	Troth	15	10
	ND	Amenia	14	13
	ND	Durbin	16	12
	NE	Brandes	28	22
	NE	SCAL	23	31
	WI	Steuben	22	27
	WI	Wauzeka	25	25
2015	IA	Boone	21	42
	IA	Lewis	25	26
	IL	Brown2	21	36
	IL	Urbana2	16	28
	IN	Loam2	33	28
	IN	Sand2	15	33
	MN	New2	32	38
	MN	Charles2	22	28
	MO	Lonetree	33	36
	MO	Troth2	17	28
	ND	Amenia2	22	20
	ND	Durbin2	13	14
	NE	Brandes2	20	24
	NE	SCAL2	41	12
	WI	Belmont	19	12
	WI	Darling	22	27

Table 4.8. Soil and weather information used to adjust the MU algorithm for all 32 sites. The amount of irrigation was included in total precipitation (PPT) for sites with irrigation.

Year	State	Site	EONR	GDD	SOM	Clay	PPT	PAWC	SDI
			kg N ha^{-1}		----g $100g^{-1}$----		cm	cm m^{-1}	
2014	IA	Ames	155	497	1.8	21	25	25	0.64
	IA	Mason	153	571	2.2	23	33	31	0.66
	IL	Brown	237	495	0.9	15	22	35	0.68
	IL	Urbana	263	469	1.9	26	27	35	0.68
	IN	Loam	172	427	1.3	23	25	21	0.65
	IN	Sand	192	422	0.8	9	28	18	0.64
	MN	New	158	488	3.6	31	28	29	0.58
	MN	Charles	117	508	1.5	18	24	41	0.61
	MO	Bay	177	540	1.2	24	17	33	0.58
	MO	Troth	188	584	0.9	23	15	36	0.60
	ND	Amenia	164	504	2.1	20	14	28	0.68
	ND	Durbin	165	486	3.2	49	16	19	0.67
	NE	Brandes	205	623	0.7	7	28	11	0.65
	NE	SCAL	138	503	1.7	30	23	32	0.55
	WI	Steuben	77	453	2.0	23	22	42	0.60
	WI	Wauzeka	119	466	1.3	17	25	39	0.55
2015	IA	Boone	187	474	2.0	21	21	26	0.67
	IA	Lewis	107	640	1.8	31	25	37	0.63
	IL	Brown2	124	542	1.0	15	21	36	0.54
	IL	Urbana2	237	504	1.9	26	16	37	0.59
	IN	Loam2	160	416	1.6	23	33	24	0.70
	IN	Sand2	206	418	0.8	9	15	20	0.67
	MN	New2	151	471	3.4	30	32	30	0.64
	MN	Charles2	166	472	1.4	18	22	42	0.70
	MO	Lonetree	314	604	1.4	24	33	34	0.75
	MO	Troth2	314	520	1.4	28	17	27	0.65
	ND	Amenia2	155	313	1.3	15	22	26	0.63
	ND	Durbin2	139	334	3.4	49	13	30	0.65
	NE	Brandes2	198	599	0.7	6	20	10	0.65
	NE	SCAL2	27	509	2.0	30	41	33	0.59
	WI	Belmont	15	478	1.7	26	19	43	0.70
	WI	Darling	174	484	2.2	22	22	37	0.72

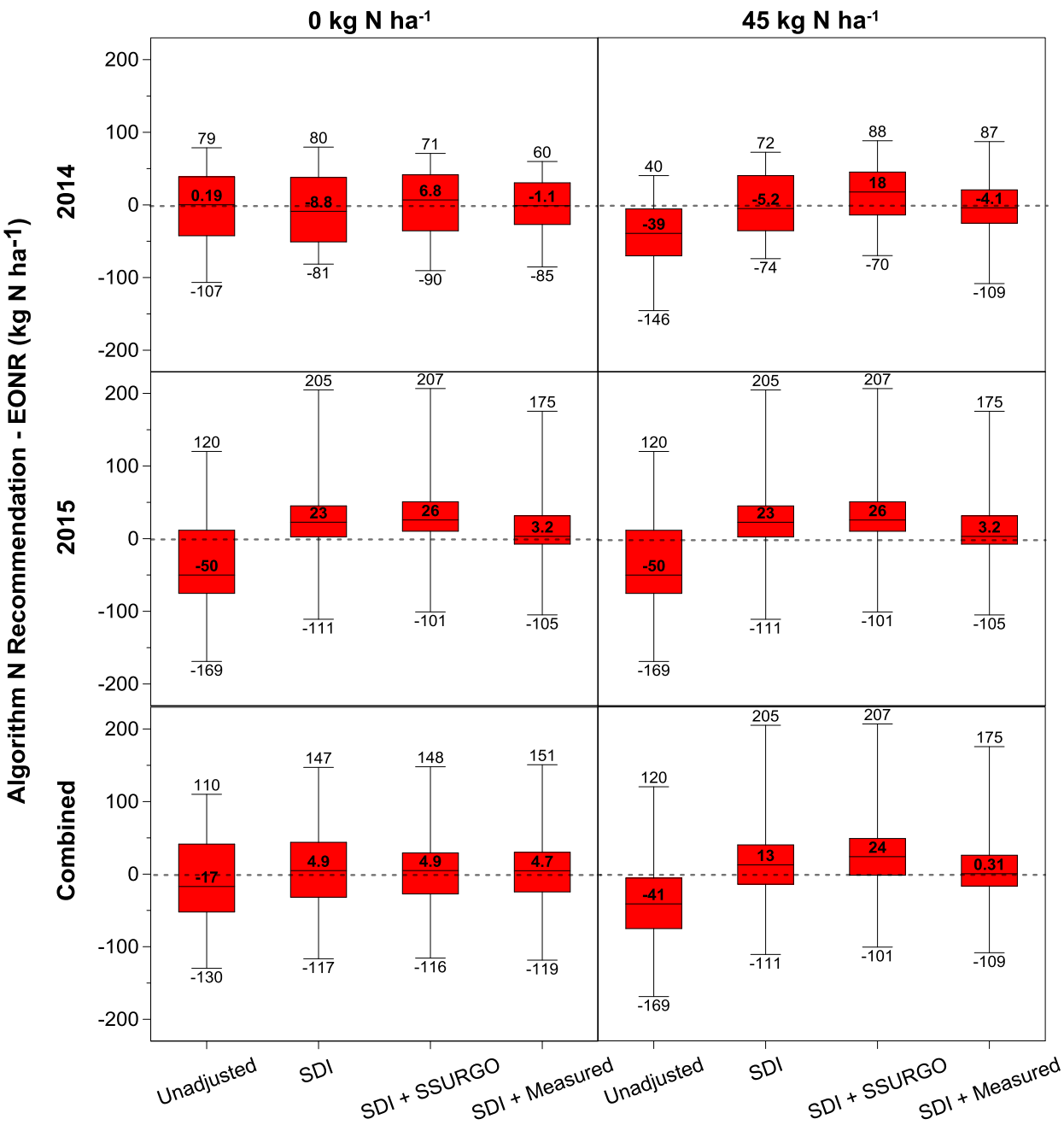

Figure 4.3. Difference between EONR and the N recommendations for 32 sites during the 2014 and 2015 growing seasons, contrasting four algorithms with no N applied at planting (left column) and 45 kg N ha^{-1} (right column). Accuracy is represented by alignment of the box median line to a difference = 0. Precision is represented by box size and whisker length. At both N rates, the adjusted University of Missouri (MU) algorithm performed the best when soil or weather information was added. A clear improvement in accuracy and precision was found going from the 45 kg N ha^{-1} to the 0 kg N ha^{-1} at-planting fertilizer rates. Algorithm performance was better during the 2014 growing season than the 2015 growing season.

Table 4.9. The mean and RMSE for the difference between the algorithm N recommendation and EONR are presented. Results are presented by growing season and combined over growing seasons. Negative and positive mean values indicate an under- and over-estimation, respectively, in the N rate recommendation. Lower RSME values indicate greater precision.

Target N Treatment	**Year**	**Algorithm**	**Mean**	**RMSE**
kg N ha^{-1}			———kg N ha^{-1}——	
0	2014	MU	-6	53
		$MU_{weather}$	-4	50
		MU_{SSURGO}	-2	46
		$MU_{Measured}$	-5	40
	2015	MU	-8	73
		$MU_{weather}$	7	64
		MU_{SSURGO}	5	60
		$MU_{Measured}$	7	62
	Combined	MU	-7	63
		$MU_{weather}$	1	57
		MU_{SSURGO}	1	53
		$MU_{Measured}$	1	52
45	2014	MU	-45	66
		$MU_{weather}$	0	42
		MU_{SSURGO}	14	45
		$MU_{Measured}$	13	45
	2015	MU	-39	84
		$MU_{weather}$	23	74
		MU_{SSURGO}	32	75
		$MU_{Measured}$	9	60
	Combined	MU	-42	76
		$MU_{weather}$	12	60
		MU_{SSURGO}	23	61
		$MU_{Measured}$	1.2	53

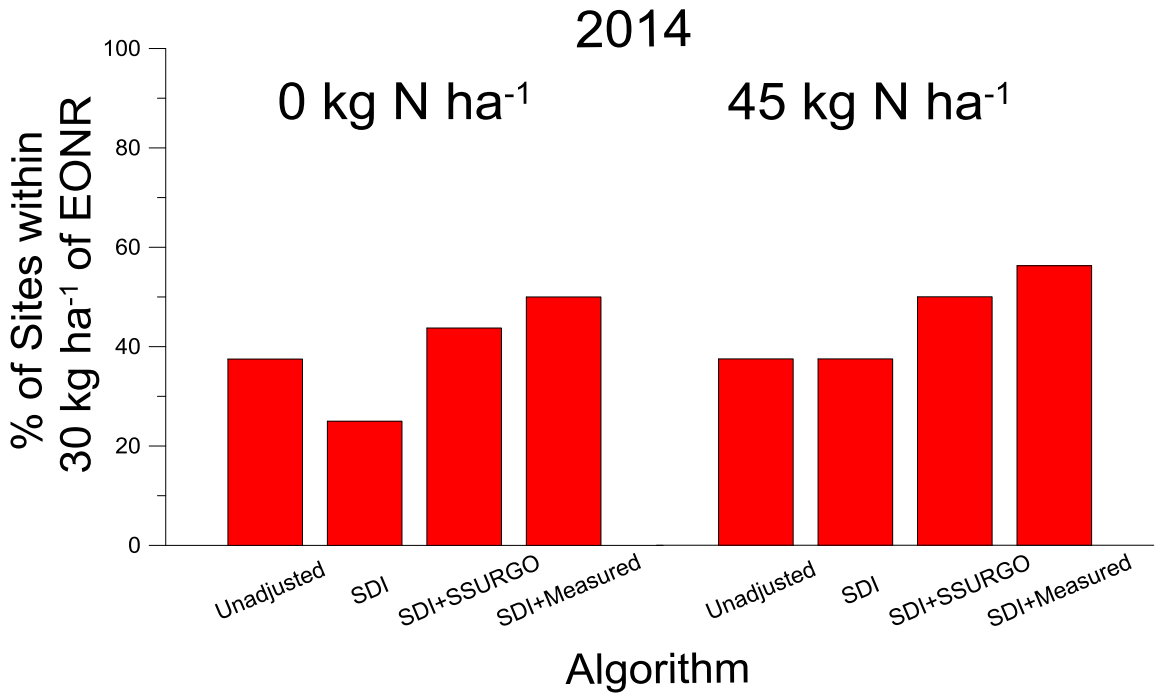

Figure 4.4. The percentage of 2014 sites within 30 kg N ha^{-1} of the economic optimum N rate (EONR), contrasting four algorithms with no N applied at planting (left cluster) and 45 kg N ha^{-1} applied at-planting(right cluster). Algorithm performance is evaluated based on the height of the bar. Taller bars suggest a larger percentage of sites were within 30 kg N ha^{-1} of EONR. As soil information was used to adjust the MU algorithm, more sites fell within 30 kg N ha^{-1} of EONR. Weather information alone did not improve the MU algorithm.

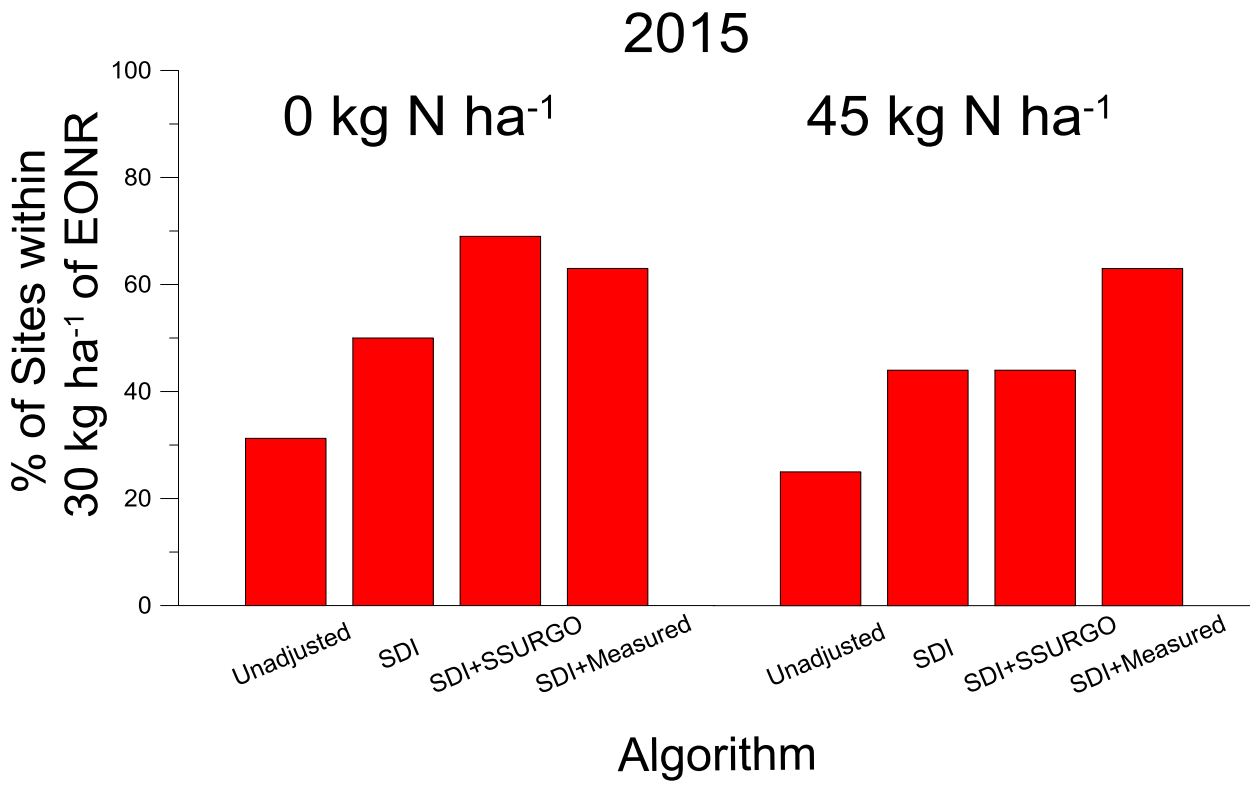

Figure 4.5. The percentage of 2015 sites within 30 kg N ha^{-1} of the economic optimum N rate (EONR), contrasting four algorithms with no N applied at planting (left cluster) and 45 kg N ha^{-1} applied at-planting (right cluster). Algorithm performance is evaluated based on the height of the bar. Taller bars suggest a larger percentage of sites were within 30 kg N ha^{-1} of EONR. As soil and weather information was used to adjust the MU algorithm, more sites fell within 30 kg N ha^{-1} of EONR.

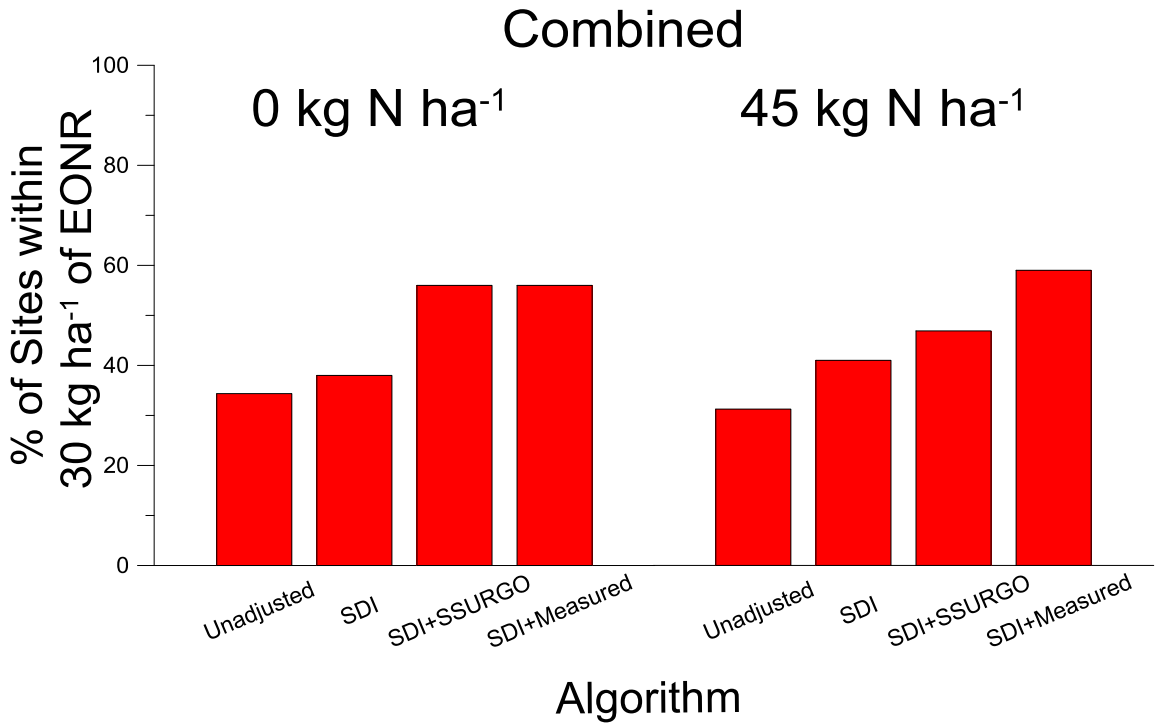

Figure 4.6. The percentage of 2014 and 2015 sites within 30 kg N ha^{-1} of the economic optimum N rate (EONR), contrasting four algorithms with no N applied at planting (left cluster) and 45 kg N ha^{-1} applied at-planting (right cluster). Algorithm performance is evaluated based on the height of the bar. Taller bars suggest a larger percentage of sites were within 30 kg N ha^{-1} of EONR. Added weather information increased the percentage of sites within 30 kg N ha^{-1} for the 45 kg N ha^{-1} target corn. As soil information was used to adjust the MU algorithm, more sites fell within 30 kg N ha^{-1} of EONR at both target corn N rates

Conclusion

In an attempt to achieve maximum yield, nitrogen (N) fertilizer is often over-applied in corn (*Zea mays* L.) production resulting in profit loss and environmental pollution (Ribaudo et al., 2011). The timing of N fertilizer applications with periods of rapid N uptake, while simultaneously applying the correct amount of N to reach the economic optimum N rate, decreases the risk of N loss (Roberts et al., 2012). Spatial and temporal variability found within fields makes this challenging. In an effort to indirectly account for this diversity, canopy sensors, an adaptive N management tool, and the algorithms that run them have been developed. Success in reducing N loss while maintaining or improving yield has been seen using canopy sensors (Scharf et al., 2011; Kitchen et al., 2010). The interaction between soil and weather variables are numerous and complex partially explaining the mediocre success seen in chapter two of this thesis and by others. However, following the incorporation of soil and weather information into the University of Missouri algorithm N recommendations improved in matching the EONR (chapter 4 of this thesis).

Simply put, a difference must be detected between the N-deficient target corn and the N-sufficient reference corn otherwise recommendations need adjustment. If, at the time of sensing, the target corn does not show any signs of N stress resulting in similar greenness and biomass between the target crop and N-reference crop, and N stress is thought to develop later in the growing season, then the algorithm needs to be informed and adjusted with soil and weather information. Differences in algorithm

performances between growing seasons are attributed to the amount of precipitation from the time of sensing to the time of plant maturity. Most recommendations by the MU algorithm adjusted with measured soil data out-performed those by the SSURGO adjusted algorithm; however SSURGO soil variables are easier and less expensive to collect. The increased performance by the measured soil variables may need a more careful economic analysis to justify the added time and money it takes to collect the samples.

Other soil and weather variables not mentioned or explored with this research may also be considered for modifying the MU algorithm for improved N fertilizer recommendations. Significantly, this work demonstrated that using soil and weather information improved the MU algorithm recommendation and demonstrated the need to fuse variability on a micro scale using the canopy sensor to variability on a macro scale by directly incorporating soil and weather information into the canopy sensor algorithm. Even though these adjustments did not produce consistent results across all sites, the approach that strategically addresses these different scales of variability may be the best way to supply sufficient N to optimize growers' profits and minimize N loss to the environment. Further, this same approach should be tried with other corn canopy sensor algorithms to see how it impacts their performance.