Estimating Nitrogen Requirement of Grain Corn in Manitoba Using Optical Spectral Reflectance

By

Claudia Quilesfogel-Esparza

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Department of Soil Science
University of Manitoba
Winnipeg, Manitoba

ABSTRACT

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Optical sensors can measure optical (visible/near-infrared) reflectance and be used to assess crop canopy conditions. In this study, two hand-held active sensors (GreenSeeker® and CropCircle™) and a passive aerial sensor (Red-Edge multi-spectral camera) were compared at three growth stages of grain corn (V4, V8 and V12) to predict in-season nitrogen (N) requirement. Active optical sensors have a light source. Passive sensors rely on sunlight; thus, their reflectance measurements are subject to changing sunlight conditions. Here a high reflectance area of canopy non-limited by N was used to standardize for variations in sunlight conditions between measurements days.

The Normalized Difference Vegetation Index (NDVI) for all three sensors and the Normalized Difference Red-Edge index (NDRE) using the CropCircle™ and Red-Edge were also compared. Four site-years (2018-2021) of N response trials were combined to capture N response under different meteorological conditions and create a regional response model, adjusted for N fertilizer and corn grain prices to determine the optimum N rate to apply. Measured grain yield significantly increased (${}_{adj}R^2$=0.40) with N supply (spring soil nitrate plus N rate). The maximum return to nitrogen (MRTN) using a current high price ratio ($N: $Corn) of 9.15:1 was 177 kg N/ha for 7,986 kg grain/ha. Two methods were used to make N addition recommendations. The first was using a quadratic response model for grain corn yield to N supply. The second was the optical sensor approach compared the difference between a non-limited area and the field estimate using canopy spectral reflectance. The optical sensor approach (187 kg/ha N) was the closest to the determined MRTN of 177 kg N/ha.

Standardizing light conditions at V4 provided significant associations of NDVI and NDRE with yield regardless of the sensor. At V8, only Red-Edge NDVI and NDRE were improved by standardization. Standardization had no effect at V12. For determining in-season N addition to grain corn in Manitoba, it is best to determine NDRE using the CropCircle V12 ($_{adj}R^2$ = 0.62). However, it is recommended for Manitoba farmers to standardize reflectance values to an N non-limited crop area as they prefer earlier timing for top or side-dressing corn between the V4 to V8 developmental stages.

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FOREWORD

This thesis was written in manuscript format using the guidelines for graduate students in the Department of Soil Science, University of Manitoba. Chapter one is an introduction and review of literature. Chapter 2 focused improving corn grain yield predictions using canopy spectral reflectance and MRTN. This study is part of a wider research proposal across Canada involving the 4R Nitrogen Management of corn.

Table Of Contents

LIST OF TABLES

Table Page

LIST OF FIGURES

LIST OF ABBREVIATIONS

Abbreviation	Explanation
N	Nitrogen
V4	four leave collars present in corn plant
V8	eight leaf collars present in corn plant
NUE	Nitrogen Use Efficiency
EONR	Economic Optimum Nitrogen Rate
MRTN	Maximum Return to Nitrogen
NIR	Near infra-red
VI	Vegetation Indices
RE	Red edge
NDVI	Normalized Difference Vegetation Index
NDRE	Normalized Difference Red-edge Index
UAV	Uncrewed Aerial Vehicle
GBS	Ground Based Sensors
High-N	High nitrogen reference area
FGUE	Fertilizer Grain Use Efficiency

1.0 Introduction

1.1 Importance of Nitrogen In Corn Production

Corn is an important staple food for both human and animal nutrition (Camberrato and Nielsen 2019). North America is a key player in the world's corn production (Omonode et al. 2017). Due to Manitoba's short growing season, little corn was grown before 1978. The corn grown was for animal feed. Genetic improvements in hybrid seed enabled increased corn production in Manitoba to meet growing demands from the livestock and ethanol fuel industries (Havlin et al. 2014; Schmidt et al. 2011).

All crops require a certain amount of N to grow; however, corn requires considerably larger quantities of N than most crops (Tagarakis and Ketterings 2017). The importance of N in corn production is due to its role in forming chlorophyll and being the primary component of protein (Alotaibi et al. 2018). To maximize grain corn production, N is required (Gardiner 2022) and insufficient N can lead to lower quality grain and lower yields (Sawyer et al. 2006). Most soils lack sufficient plant-available nitrogen (N), an essential plant nutrient (Camberrato and Nielsen 2019). The Canadian Prairies that include Manitoba, Saskatchewan and Alberta are the main grain-producing provinces in Canada and make up 80% of all synthetic N fertilizer application in Canada. Synthetic fertilizer has facilitated a 30-50% increase in crop yield and will contribute more as the global population continues to grow (Tenuta et al. 2016; Wood 2018). Increases in synthetic N fertilizer application has led to an increase in food security. Depleted soil nutrients, low yield and global food scarcity can often be linked to insufficient N inputs (Vonk et al. 2022). Nitrogen is often the yield-limiting nutrient and addition of fertilizer N is a significant cost to growers in corn production. Excessive N application decreases N use efficiency in corn and is an unnecessary cost to producers. For every increment of fertilizer applied, the yield response declines and a decrease in the proportion of plant N uptake occurs (Gardiner 2022).

Farmers tend to over-apply N fertilizer, hoping to overcome soil nitrate losses (Scharf and Lory 2002; Dias Paiao 2017). Excess N fertilizer can contaminate surface and groundwaters and contribute to greenhouse gases (Kuang et al. 2019; Rogovska et al. 2019; Gabriel et al. 2017; Chen et al. 2010). Applying very high levels of N can negatively impact growth and crop quality by increasing the amount of lodging due to formation of heavy lush leaves and increasing susceptibility to diseases. Plants with access to high levels of available N can delay the rate of development and increase the amount of time from planning to maturity (Manitoba Agriculture 2007). However, applying N fertilizer at a rate in excess to crop N needs (Sela et al. 2017) has been and continues to be done as a form of *insurance* (Scharf and Lory, 2002). Today, the biggest challenge in producing corn is making timely fertilizer application decisions that are not linked with large quantities of N fertilizer being lost to the environment (Sawyer et al. 2006; Bean et al. 2018). A farmer who is walking through their corn fields early in the season, when most of the corn plants have 4 leaf collars (V4) is interested in knowing how much Nitrogen (N) to apply while still making a profit.

1.2 Soil N Mineralization

Soil N can become available to crops through mineralization from soil organic matter. Mineralization plays a role in determining N fertilizer application rates because N that is mineralized from organic matter becomes available to crops during the growing season (Sawyer et al. 2006). However, rates of organic matter mineralization vary among soils and even within soils, making it challenging to predict N contributions within fields. The inherent complexity of determining mineralization of soils organic matter content in mineral soils is often why it is excluded from N fertilizer recommendations (Paiao et al. 2020; Sawyer et al., 2008). The rates of N mineralization are key to determining the amount of soil N released and made available to a crop during the growing season. There is a large uncertainty in soil N supplied during the growing season. Flaten and Mangin (2018) found that a pre-plant nitrate-N test did not provide an accurate prediction of the N that would be made available through mineralization. The uncertainty in how much soil N will be available throughout the growing season would make applying sufficient N at planting along with an in-season reassessment of the yield goal and N demands to reach that goal beneficial (Flaten and Mangin 2018; Flaten and Gardiner 2019).

1.3 Corn Development Stages

The developmental stages of corn are broken into two main categories: vegetative and reproductive. In the vegetative stage, visible collars at the base of the leaves are used to defined growth stages. A collar is a leaf blade attached to the stem of the plant. From emergence to tasselling, corn growth stage is defined by the number of collars on the plants. A V5 stage is defined by 5 leaf collars present on the plant. The V10 stage would have 10 collared leaves on most plants. The completion of the vegetative stage occurs when tassels eventually appear at the top of the corn (VT) where pollen will. There are six reproductive stages of corn labelled R1 through R6. The R1 silking stage occurs when silks start to appear on the outside of the corn husk and catch the pollen from the tassel. Blistering (R2) occurs when new fertilized kernels emerge that are white and consist of 85% moisture. Yellow kernels are a sign of the milk (R3) due to a milk-like liquid in the kernels occurring because of starch accumulation. The dough stage (R4) is marked by thickened kernels due to starch accumulation. When kernels are squeezed together as they grow, they have a dough consistency. Dent (R5) occurs when moisture decreases, and small dents appear in the kernels as they shrink. The final stage is maturity (R6), when all kernels have attained their maximum dry weight and can have a grain moisture content of 31-35% depending on hybrid and environment (Ciampitti et al. 2011; Manitoba Crop Alliance 2021).

1.4 Corn Nitrogen Demand in Manitoba

The most critical time for N to be supplied and taken up by the corn plant is before the silking stage. Nitrogen supplied to the corn before silking occurs will make up the majority (84%) of N found in the grain (Stanford and Legg 1984). Corn takes up the greatest amount of N mid-July to early August in Manitoba, which coincides with the V8-VT growth stages. Roughly 50% of total N uptake occurs during this time. Corn is a warm, longer season crop with a rapid N uptake (Heard and Hay 2004). When corn is seeded it consists of only 7-9 kgs of dry matter and in a few weeks those seeds become an energy-capturing factory that will have produced 9,072 kgs of dry matter and created 500-1000 new seeds from the planted seeds. From emergence to V4, the crop approximately doubles its dry weight. At V4, a corn field will have accumulated only 1.12 kg N/ha. Before reaching the tassel stage 9,000 to 10,000 lb/acre of plant biomass is generated in the preceding five to six weeks of growth and roughly 60-70% of total N uptake occurs by this stage. From tassel to maturity, plant biomass doubles again to 22,417 kg/ha with around half of the above-ground weight coming from grain. Once the corn has reached the silking and kernel blistering stage, N uptake slows until the dent stage when there is translocation of nutrients and carbohydrates into the developing kernel in the grain filling stage (Sawyer et al. 2006). Applying N in-season can provide an opportunity to better determine crop price and growing conditions so that growers can apply supplemental N fertilizer at a rate that can maximize potential profits (Manitoba Agriculture 2007).

1.5 Nitrogen Fertilizer Efficiency

Nitrogen use efficiency (NUE) is a ratio of N reclaimed in the harvested product to N applied (Rhezali and Lahlali 2017; Thompson and Puntel 2020). It is a measure of how much N applied to the soil was taken up and remained in the plant (Sharma and Bali 2017). For farmers to reduce cost and improve the efficiency of N fertilizer, application should mimic crop demands (Gabriel et al. 2017). Several factors can contribute to a low NUE including (1) not matching fertilizer application with (2) as well as not considering spatial and temporal variability in soil-available N and crop N demand (Thompson and Puntel 2020). The goal of N efficiency for corn grain production is to optimize NUE to reach the most economic yield. Having a higher efficiency is tied to better 4R management (Augarten et al.2019); the 4R's being: Right application, Right amount, Right time and the Right place. For the 4R's to reach best management practices all 4Rs must be considered for a specific farm, field, environment and economic goal and must be measured and continually adapted and improved (Mulla 2013; Hunt and Daughtry 2018; Fixen 2020). It is estimated that 50-70% of N fertilizer applied is lost (Masclaux-Daubresse et al. 2010). In Canada, crops can take up less than 50% of the N fertilizer applied per season and approximately 65% over five growing seasons (Holzapfel 2007). In Alberta, about 30-50% of all applied N fertilizer is taken up by the crop (Mezbahuddin et al. 2020).

A plant's ability to utilize existing available N depends on its environment and soil type. To maximize NUE and match N application to crop N demand, the different N sources that make up crop production, the interaction between available soil N, how N can be taken up, stored or lost, crop genetics management impacts and weather conditions need to be considered (Congreves et al. 2021;Wood 2018). Meaningful metrics that identify environmental and economic impacts to reduce nutrient losses while minimizing excessive N inputs are needed. Nitrogen use efficiency is a valuable metric to identify, monitor and develop management practices that reduce N losses.

What NUE does not encompass is system susceptibility to losses over time and rather emphasizes yield which misleadingly quantifies only the plant tissue fate of N without capturing N cycling. There is a temporal and spatial component to NUE and measurements from a single growing season can provide only limited crop and site-specific information. Alternatively, multiple site-years of measurements describes the productivity of a cropping system over time. Not considering excess N in relation to crop demand and ignoring residual fertilizer N or additional N applications over time can underestimate or overestimate NUE (Congreves et al. 2021). Available moisture throughout the growing season significantly affects crop response to available N. When soil moisture levels are limited, higher moisture results in higher yield with the same N levels and a greater response to N fertilizer applied. Lower moisture limits plant yield response but results in higher protein content (Manitoba Agriculture 2007). Having a moisture deficit reduces NUE and thus yield because less soil organic matter mineralization occurs. Mass flow movement of nitrate-N to the root is impeded when there is a lack of soil water. Under drought conditions corn grain yield will be reduced and require more N per bushel (Heard 2022).

1.6 Current Nitrogen Recommendations in Manitoba

The importance of grain yield forecasting and modeling is to provide fertilizer recommendations (Holland et al. 2010). The aim of having N recommendations is to accurately estimate the difference between N available in the soil and N needed by the plant (Holzapfel et al. 2009; Dias Paiao 2017).

1.6.1 Target Yield

Managing N for corn production is different around the world because of differences in soil characteristics, weather, hybrids and expected yield (Rhezali and Lahlali 2017). Yearly differences in meteorological conditions lead to varying responses to N application (Paiao et al.

2020). Organic N Mineralization is often highlighted as a major source of N to corn (Niemeyer et al. 2021). The ability to accurately predict soil nitrate fluctuates depending on temporal and spatial variations and is particularly susceptible in rainfed production due to variations in N mobility with changing moisture conditions (Puntel et al. 2018). To be able to make N recommendations, factors like precipitation, timing of precipitation, N source and seed variety need to be considered because they contribute to grain yield (Morris et al. 2018). Crop N requirement is dependent on the species of the crop and yield goal and is reliant on the weather conditions throughout the growing season like precipitation and temperature. Historical yield and soil fertility data is required to make crop N requirement predictions (Gardiner 2022). It is important to conduct N rate studies across a range of soil and precipitation conditions.

In Manitoba pre-plant soil nitrate levels are used to make N fertilizer recommendations. Total N, spring nitrate-N plus N applied at planting, need to be considered when evaluating the effect on yield because it accounts for spring soil nitrate levels that change yearly. The importance of knowing spring soil nitrate levels is to account for total N and optimize N fertilizer application (Heard 2022; Manitoba Agricultural 2007). Using yield goals as a basis for fertilizer recommendation can over or underestimate actual nutrient requirement of crops year to year. There is a limitation to the yield goal approach because of the uncertainty in estimating yield potential and the amount of N available in the soil (Holzapfel et al. 2009; Dias Paiao 2017). No one tool is perfect for making N rate recommendations however, region specific models can improve N management decisions (Gardiner 2022). Manitoba Agriculture provides tools to help producers determine the appropriate N rate based on a target yield selected by producers. Once a target yield has been selected a N recommendation is given based on local research. Recommendations are based on a crop’s N requirement and difference in the existing pre-plant soil nitrate-N. The Manitoba Soil Fertility Guide, last updated in 2007, provides target yield for corn up to 8,743 kg/ha which was determined by using a target yield to come up with the N rate to reach that yield (Manitoba Agricultural 2007).

1.6.2 Economic Optimum Nitrogen Rate

The objective for reaching the Economic Optimum Nitrogen Rate (EONR) is to apply enough N to receive the maximum return on the price of applying N to grow the crop. This is especially important for corn since applying excess N comes at a financial loss in surplus soil NO_3^- postharvest (Schmidt et al. 2011). Making fertilizer recommendations that only take into account or neglect to consider yield explained less than 50% of the variations in EONR for corn. Nitrogen use efficiency and yield both need to be considered if more than 50% of variations in EONR are to be addressed (Lory and Scharf 2003; Arnall et al. 2013). Efficient N use requires identifying the appropriate N rate that maximizes the return on nitrogen, optimizing yield and minimizing adverse environmental impacts. The maximum return to nitrogen (MRTN), an economic maximum return for N application, is crop dependent and varies with environmental conditions, agricultural practices and crop prices. Soil texture also plays a role in N efficiency. Corn grain yield in coarse-textured compared to fine-textured soils has been reported to be higher (Alotaibi et al. 2018). A good measure for efficiency of N fertilizer rate applied is the residual nitrate levels in the soil post-harvest in fall. High residual fall N levels decrease the rate of N applied to reach MRTN (Alotaibi et al. 2018; Sawyer 2006) in the following years. The presence of NO_3^- post-harvest means some of the N fertilizer applied was not taken up by the crop (Schmidt et al. 2011). Manitoba Agriculture published EONR for corn using multiple site years of yield data under low and high precipitation with yields greater than 8,743 kg/ha (Heard 2022). Combining data across sites with different growing season moisture conditions provides insight into the variation of crop yield response to fertilizer N with differences in soil moisture. Prior to planting, growers do not know if the growing season will be dry or wet. There is a risk with fall or early spring N application because the crop yield response will vary depending on the soil moisture available during the growing season. Crop yield response to fertilizer N, N costs and crop prices are used to determine the EONR. From the yield response to N rate, the N requirement can be estimated based on the price ratio of Fertilizer \$ kg^{-1} N to Corn \$ kg^{-1}.

1.6.3 Field Level Predictions

Reflectance algorithms are mathematical formulas that transform reflectance readings to in-season N recommendations (Dias Paiao 2017; Hoffmann et al. 2016). The algorithms are developed for active sensors and require a high nitrogen (High-N) non-limiting area (Sharma et al. 2015). All in-season N recommendation algorithms compare target and optimum corn using a combination of R, NIR and RE bands. Nitrogen induced stress can be subtle and "visually difficult to quantify" without a reference strip (Franzen et al. 2016). To compare areas in a field, non-limiting N areas need to be established. Nitrogen management using sensor readings use the difference in reflectance readings between corn with sufficient N fertilizer (High-N) and unfertilized or deficient corn (Bean et al. 2018; Mulla 2013). The concept has been successfully demonstrated in previous research using sensors and algorithms to predict N (Solie et al. 2012; Sripada et al. 2006; Holzapfel et al. 2009; Baral and Adhikari 2015; Franzen et al. 2016, 2019; and Bean et al. 2018). There are three steps to estimate grain corn fertilizer requirements using optical sensors. First, the yield potential of corn should be estimated. Second, the yield potential of corn should be estimated under sufficient N. Lastly, if N deficiencies are apparent, the differences between the high N reference and other areas of the field are used to calculate the supplemental N fertilizer application rate required to correct the N shortage (Holzapfel 2007; Raun and Johnson 2002).

Grain corn N response varies with differences in available soil N, NUE, crop N uptake and losses (Lory and Scharf 2003; Ransom et al. 2020). Selection of the suitable optimum fertilizer N rate requires fitting grain corn N yield response models (Cerrato and Blackmer 1990). The decision on what algorithm to choose depends on the region and farming practices (Franzen et al. 2019). There exist numerous N fertilizer rate prediction tools to help farmers make better N management decisions including the Maximum return to N (MRTN) (Sawyer et al. 2006) and Stanford mass balance method (Stanford 1973; Sela et al. 2017). The MRTN, an economic maximum return to applying N, is crop dependent and varies with environmental conditions, agricultural practices and crop prices (Alotaibi et al. 2018; Sawyer 2006). The MRTN calculation can be updated to reflect current corn and fertilizer prices. A limitation with MRTN is its inability to address year-to-year variability in soil N supply and to predict site-specific N requirements. Canopy reflectance sensing can provide in-season real-time assessment of N corn status along with within field variability. A constraint of sensors is the need to have reference areas to compare to the target area because it can be difficult to detect slight N deficiencies (Ransom et al. 2020).

Stanford (1973) and Meisinger (1984) were the first to publish the yield-based fertilizer N recommendations (Lory and Scharf 2003). Stanford (1984) outlined that to estimate N fertilizer needs, crop N requirements are needed. The N requirement was defined as the minimum quantity of N in the biomass that contributed to the maximum production. Analyzing total biomass of corn stover plus grain, the N requirement of corn was 1.2% with grain making up 54% of total biomass. An efficiency factor of 70% of applied N being taken up was assumed (Stanford and Legg 1984). The yield-based equation estimated the EONR at a selected yield goal (Lory and Scharf 2003). The Stanford mass balance equation is guided by crop yield potential, N cycle and N efficiency uptake. What makes Stanford mass balance appealing is the site-specific N recommendations based on soil and crop N, along with the ease of use. The model limitations include over generalization and fall short of field specific EONR, it is static neglecting the interactions between the weather and soil N dynamics (Sela et al. 2017).

The Yield-based equation (Lory and Scharf 2003) is:

(1.1) Nf = (Ng -Ngs)/FNUE

where Nf is the estimated ENOR at a selected yield, Ng is the N content in grain harvest, Ngs is soil N in grain and FNUE is fertilizer N use efficiency of the grain

Fertilizer nitrogen use efficiency was calculated by plotting EONR as the independent and predicted N rate as the dependent variable (Lory and Scharf 2003).

1.7 Optical Sensors

The chlorophyll meter was the first sensor used to assess available crop N by measuring light transmitted through a leaf at around 650-940 nm wavelength. The meter worked under the principal that N-deficient corn had reduced leaf chlorophyll content that increased leaf light transmittance (Blackmer et al. 1996b). Chlorophyll concentrations influenced how light is absorbed or reflected. Visible light reflected, increases with N deficiencies because chlorophyll is efficient at absorbing visible light (Blackmer et al. 1996a). The best way to translate sensor readings were to express them relative to an in-field reference area under nonlimiting N. Chlorophyll meters can assess leaf transmittance in a few minutes but the technique was time consuming. An alternative was to sense light reflected from the plant canopy and, thus, assess many plants at once. Both chlorophyll meter transmittance and canopy spectral reflectance are governed by how chlorophyll interacts with light. Total biomass in a plant canopy determines the total amount of chlorophyll available for absorbing visible light, plus canopy architecture affects the shading of underlying leaves and, therefore spectral reflectance (Blackmer et al. 1996b).

Research out of the University of Nebraska in 1992 was the first to use chlorophyll meters and suggested they were superior at estimating yield than leaf N concentration (Arnall et al. 2013). In

1996 aerial photography using color film and bandpass filters were analyzed to assess N stress in corn. The raw RGB each represents a digital count that is proportional to the total reflected light. They found a good relationship between digital count and corn grain yield. They concluded that differences in grain yield and digital count did not allow for pooling across years (Blackmer et al. 1996a).

Nitrogen, a mobile nutrient can be supplemented with an in-season fertilizer application if deficiencies are present. Traditional nutrient testing methods do not account for field variability, in plant available N, which causes yield variation per field location (Holzapfel et al. 2009). Optical sensors provide a way to understand how light is intercepted and reflected by a plant canopy and convert electromagnetic radiation into indicators of N status (Mkhabela et al. 2005; Sripada et al. 2006; Viscarra Rossel et al. 2011; Gitelson 2013; Sulik and Long 2016; Puntel et al. 2018). Crops absorb solar energy during the growing season and use it to convert carbon dioxide and water into biomass (Chen et al. 2010). The sensors provide a measure of the two primary processes, absorption and reflectance (Jacquemoud et al. 2009). Living plant biomass reflects electromagnetic radiation differently at different wavelengths. The differences can be interpreted by collecting reflectance data from specific wavelength bands within the electromagnetic spectrum (Havlin et al. 2014). Plant or crop biomass, as used here, refers to the aboveground biomass expressed on a dry weight basis. Plants can exhibit N stress (deficiencies) through leaf colour. Assuming there are no other elemental deficiencies, corn leaves become progressively more yellow with greater N-deficiencies while conversely, greener leaves indicate the corn has sufficient nitrogen. The human eye can only see the visible portion of the electromagnetic spectrum. However, optical sensors can quantify visible to near infra-red (NIR) light for several different wavelength ranges. These are known as multi-spectral optical sensors. The NIR wavelength provides an important assessment of the nutritional status of growing corn that the human eye cannot see (Paiao et al. 2020). The combination of visible and NIR reflectance provides a method to make in-season N application decisions (Bean et al. 2018), done by measuring canopy spectral reflectance (Schmidt et al. 2011). This type of remote sensing involves characterizing spatial differences in corn reflectance in specific wavelength ranges (Mkhabela et al. 2005; Gitelson 2013).

Crop productivity is the result of solar energy being absorbed during the growing season and converted into biomass (Chen et al. 2010). Plant chlorophyll absorbs photons in the visible spectrum (400 to 700 nm) with peak absorbance in blue and red bands. A plant's ability to absorb or reflect light is governed by the amount of the photosynthetic pigments present in the leaf. Near infra-red is not absorbed by chlorophyll and is mainly reflected from green vegetation (Basyouni n.d.; Gabriel et al. 2017a). Plant leaf greenness is strongly related to chlorophyll content and N status. A healthy corn plant absorbs visible electromagnetic radiation mainly in the blue and red bands and reflects NIR. Unhealthy (deficient) corn has low NIR reflectance and high red reflectance (Basyouni 2017; Gabriel et al. 2017).

The strong correlation between canopy N and photosynthesis has been used as a crop N status indicator (Mulla 2013; Bean et al. 2018). Spectral leaf reflectance at different wavelengths can be used to calculate vegetation indices (VI) (Gitelson 2013). A VI is a formula that converts electromagnetic radiation captured from sensor reflectance into an index [-1 to +1] that can be used as an indicator of corn N status. As changes in biomass development occur throughout the season, so does the spectral response. By sensing the relationship between spectral response and biomass development, it is possible to distinguish if the spectral signature is indicating crop stress or changing simply due to canopy development (Barnes et al. 2000).

Throughout the growing season, crop growth and development can be monitored using changing VI values (Hochheim et al. 1998). Two common VI are the normalized difference vegetation index (NDVI, equation 1.2) (Rouse et al. 1973) and a normalized difference red-edge index (NDRE, equation 1.3) (Barnes et al. 2000). Both indices were developed for use with the reference from passive optical satellite platforms.

(1.2) $$\text{NDVI} = \frac{(\text{NIR} - \text{Red})}{(\text{NIR} + \text{Red})}$$

(1.3) $$\text{NDRE} = \frac{(\text{NIR} - \text{RE})}{(\text{NIR} + \text{RE})}$$

where NIR is near infra-red reflectance, Red is red reflectance and RE is the red edge reflectance, from wavelengths in the range between the red and NIR.

The ratio of reflectance between the visible and NIR portion of the electromagnetic spectrum is at the heart of canopy sensing (Hochheim and Barber 1998; Clay et al. 2006; Chen et al. 2010; Mulla 2013; Bean et al. 2018). For both NDVI and NDRE, corn with healthy green vegetation has high positive VI values while areas without vegetation like bare soil have near zero to negative values (Gitelson 2013; Mkhabela et al. 2005). If canopy cover can be quantified using sensors throughout the growing season, farmers can estimate N fertilizer requirements. Remote sensing can be utilized to detect N deficiencies in corn (Franzen et al. 2016). What makes corn an ideal candidate for remote sensing is that it remains green until entering the reproductive growth stage (Sulik and Long 2016).

Active sensors have their own light source, which differentiates them from passive sensors that rely on sunlight as a source of electromagnetic radiation. The crop canopy reflectance measured by passive optical sensors is subject to changes in light conditions

(Thompson and Puntel 2020) due to meteorological factors that affect incoming solar radiation (Kahimba et al. 2009). Crop reflectance obtained through cameras mounted on uncrewed aerial vehicles (UAV) images is an example of a passive sensor. Digital images constructed from either active or passive sensor measurements can be used to extract information about the crop using VI (Hoffmann et al. 2016).

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Grain corn N response varies with differences in available soil N, NUE, crop N uptake and losses (Lory and Scharf 2003; Ransom et al. 2020). Selection of the suitable optimum fertilizer N rate requires fitting grain corn N yield response models (Cerrato and Blackmer 1990). The decision on what algorithm to choose depends on the region and farming practices (Franzen et al. 2019). There exist numerous N fertilizer rate prediction tools to help farmers make better N management decisions including the Maximum return to N (MRTN) (Sawyer et al. 2006) and Stanford mass balance method (Stanford 1973; Sela et al. 2017).

The MRTN, an economic maximum return to applying N, is crop dependent and varies with environmental conditions, agricultural practices and crop prices (Alotaibi et al. 2018; Sawyer 2006). The MRTN calculation can be updated to reflect current corn and fertilizer prices. A limitation with MRTN is its inability to address year-to-year variability in soil N supply and to predict site-specific N requirements. Canopy reflectance sensing can provide in-season real-time assessment of N corn status along with within-field variability. A constraint of sensors is the need to have reference areas to compare to the target area because it can be difficult to detect slight N deficiencies (Ransom et al. 2020).

Stanford (1973) and Meisinger (1984) were the first to publish the yield-based fertilizer N recommendations (Lory and Scharf 2003). Stanford and Legge (1984) outlined that to estimate N fertilizer needs, crop N requirements are needed. The N requirement was defined as the minimum quantity of N in the biomass that contributed to the maximum production. Analyzing total biomass of corn stover plus grain, the N requirement of corn was 1.2% with grain making up 54% of total biomass. An efficiency factor of 70% of applied N being taken up was assumed (Stanford and Legg 1984). The yield-based equation estimated the EONR at a selected yield goal

(Lory and Scharf 2003). The Stanford mass balance equation is guided by crop yield potential, N cycle and N efficiency uptake. What makes Stanford mass balance appealing is the site-specific N recommendations based on soil and crop N, along with the ease of use. The model limitations include over generalization and fall short of field specific EONR and it is static, neglecting the interactions between the weather and soil N dynamics (Sela et al. 2017).

The Yield-based equation (Lory and Scharf 2003) is:

(1.1) $N_f = (N_g - N_{gs})/FNUE$

where N_f is the estimated EONR at a selected yield, N_g is the N content in grain harvest, N_{gs} is soil N in grain and FNUE is fertilizer N use efficiency of the grain

Fertilizer nitrogen use efficiency was calculated by plotting EONR as the independent variable and predicted N rate as the dependent variable (Lory and Scharf 2003).

1.8 Standardization

Canopy reflectance acquisition, is affected by sensing conditions such as canopy architecture (leaf angle, surface area and leaf structure) (Gitelson 2013), and light conditions (intensity of incoming radiation, and the influence of spectral signature from surrounding objects) which are not uniform throughout the field. Prior to being absorbed, photons typically encounter multiple scattering surfaces such as plant leaves that are influenced by canopy architecture (Rouse et al. 1973; Singh et al. 2019) and can be affected by the shadows that are cast by upper leaves (Gabriel et al. 2017). Illumination conditions are very important for passive sensors. Consistent cloud cover reduces changes in incoming radiation and results in more accurate spectral reflectance values. It is very important that passive sensors are calibrated using standard reference panels prior to data collection (Adão et al. 2017; Hunt and Daughtry 2018; Singh et al. 2019; Thompson and Puntel 2020). Sripada et al. (2006) recognized that aerial sensed images when corrected for changes in illumination levels by using a reference panel performed better than without the correction. Changes in atmospheric and illumination conditions have been an obstacle for passive sensors since their inception (Rouse et al. 1973).

Farmers need to decide N application rates early in the growing season before full canopy closure. As a crop's canopy grows, the additional biomass affects the total reflectance at different wavelengths. An area within a field with high nitrogen (High-N) has been previously used as a baseline to determine locations in the same field where nitrogen may be a limiting factor. It assumes that plant growth rate is proportional to available N. As rapid growth begins to occur, differences in biomass growth rate will be easily picked up by the sensor. The key assumption of a High-N area is that the rate of plant growth is proportional to available root zone N. As rapid growth occurs in the corn crop the difference in rate of growth can be easily measured by a sensor. Sensor measurements from the High-N area increase with growth stage development and the sensed value can be used as a measure of the potential grain yield under nonlimiting N conditions. A comparison of the reflectance from the High-N area to the reflectance from the remainder of the field provides a way to detect the areas with lower yield potential (Solie et al. 2012). High-N areas are a way to normalize sensors to quantify crop growth regardless of growth stage and incorporate in-season algorithms to predict N requirements. While the concept of using a high-N area to make in-season N recommendations is well accepted (Sripada et al. 2006; Holzapfel 2007; Holland and Schepers 2010; Franzen et al. 2016; Bean et al. 2018), the approach of using a high reflectance area to account for variations in light conditions between measurement dates has not been done for both active and passive sensors.

1.9 Objective Of the Study

Predicting corn grain yield using optical sensors is possibly a means to improve in-season N dressing recommendations by matching N rate with crop demand. To my knowledge, there are no guidelines and research for Manitoba corn growers to use canopy reflectance for N rate recommendations. There is a need for local research to determine if active and passive spectral reflectance of grain corn during vegetative growth stages is related to crop yield and could provide a basis to estimate in-season N supplementation to achieve a maximum economic return to nitrogen addition. This thesis research aimed to utilize canopy sensing to improve in-season nitrogen recommendations in Manitoba. The specific objectives of this study are to determine if (1) canopy spectral reflectance during early vegetative growth stages can predict corn grain yield, (2) standardizing spectral reflectance indices using high canopy reflectance areas improve the estimation of grain yield, and (3) standardizing spectral reflectance indices captured in early vegetation growth can estimate the in-season nitrogen dressing requirement of grain corn.

The NDVI and NDRE spectral reflectance indices were compared using ground based active reflectance sensors, GreenSeeker® (NDVI) and CropCircle™ (NDVI and NDRE), and an aerial MicaSense multi-spectral camera (NDVI and NDRE) for passive UAV-based reflectance determination. A novel approach to standardizing spectral light conditions at the time of sensing was done. The hypothesis was that standardizing light conditions would improve the ability of spectral indices to predict corn yield and in-season nitrogen dressing recommendations over multiple years. Better predictions of in-season nitrogen dressing needs are ultimately aimed at reducing losses to the environment while improving the economics of grain corn production.

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2.0 Improving In-Season Corn Nitrogen Dressing Using Canopy Sensing

2.1 Abstract

Predicting corn grain yield using optical sensors is possibly a way to improve in-season nitrogen (N) dressing additions. However, there are currently no N rate recommendations for Manitoba corn growers to use canopy spectral reflectance. Using three optical sensors to sense three corn growth stages (V4, V8 and V12) in 2018-2021, N rate trials were conducted in western Manitoba. The four-site years were combined to capture N response under different meteorological conditions and provide insight into the variation of corn yield response to fertilizer N under different soil moisture. The relationship between end-of-season corn grain yield and spring soil nitrate plus nitrogen rate (N supply) had a significant response to N fertilizer applied (${}_{adj}R^2$=0.40). The quadratic response model for the maximum return to nitrogen (MRTN) under the high price ratio was 7,986 kg corn grain ha^{-1}, requiring 0.0222 kg N kg^{-1} corn.

The Normalized Difference Vegetation Index (NDVI) and the Normalized Difference Red-Edge index (NDRE) spectral reflectance indices were compared using active reflectance sensors, GreenSeeker® (NDVI only), CropCircle^{TM}, and a passive sensor (Red-Edge multi-spectral camera) UAV-based reflectance at three corn growth stages. To account for variations in light conditions between measurement dates active and passive reflectance was standardized using a high reflectance area (High-N).

Standardizing light conditions at V4 provided significant associations of NDVI and NDRE with yield regardless of the sensor. At V8, only Red-Edge NDVI and NDRE were improved by standardization. Standardization had no effect at V12. For determining in-season N addition to grain corn in Manitoba, it is best to determine NDRE using the CropCircle at V12 (${}_{adj}R^2$ = 0.62). However, it is recommended for Manitoba farmers to standardize reflectance values to an N non-limited crop area as they prefer earlier top or side-dressing corn at V4 to V8.

2.2 Introduction

Nitrogen tends to be over applied at more than the recommended rate to overcome potential soil nitrate losses (Scharf and Lory 2002). This increases the cost of production and can adversely affect the environment. Choosing an optimum N rate to meet crop demands is both of economic and environmental benefit (Janovicek et al. 2021). Nitrogen fertilizer prices were bullish in 2022 in the United States and Canada (Mcewan and Marchand 2022) . However, corn prices were also high, which meant that corn in crop rotations was still profitable (Heard 2022). Nitrogen is an expensive crop input and growers may want to delay N application until after they can better determine the yield potential and assess whether soil moisture is sufficient to increase the yield benefit from additional N (Heard and Hay 2004).

In Manitoba, N fertilizer can be applied in the spring, at or near planting or more commonly in the preceding fall when fertilizer costs tend to be lower and when drier soil conditions facilitate field access for application. Late fall-applied N when soil temperature is below 5˚ C is the best time for fall N application (Manitoba Agriculture 2007; Tenuta et al. 2016). Corn is a warm, longer season crop with a rapid N uptake. The greatest amount of N is taken up mid-July to early August in Manitoba, which coincides with the V8-VT growth stages. Roughly 50% of total N uptake occurs during this time (Heard and Hay 2004). Thus, it is not critical to have a large amount of fertilizer N applied by planting time.

Remote sensing can characterize spatial differences in the growth and development of crops (Gitelson 2013; Mkhabela et al. 2005) and provide a dynamic way for farmers to characterize spatial differences in the growth and development of crops (Sripada et al. 2006; Viscarra Rossel et al. 2011; Puntel et al. 2018; Sulik and Long 2016). While the convention for plant and soil nutrient sampling is through destructive methods, remote sensing provides a non-destructive way to convert reflected electromagnetic (EM) radiation into N status indicators.

Optical sensors measure EM radiation that is reflected from a surface at visible and near infra-red (NIR) wavelengths. Active optical sensors have their own light source which is used to illuminate a surface and create reflected EM radiation from the surface. Passive sensors rely on sunlight as a source of EM radiation (Franzen et al. 2019) and, thus, their EM reflectance measurements from a surface are subject to changing sunlight conditions.

Optical sensors are designed to measure reflected EM radiation in specific wavelength ranges. The amount of reflected radiation in Red (~ 650 nm wavelength), NIR (> 800 nm) and red-edge (700 to 800 nm wavelength) ranges have been used for decades to determine the biomass and status of green vegetation (Rouse et al. 1973). Two common vegetation indices (VI) are the normalized difference vegetation index (NDVI) and a normalized difference red-edge index (NDRE). Normalized Difference Vegetation Index is the most common VI, developed with a focus on quantifying living biomass and has a long history of being used to monitor crop status and forecast yield (Sulik and Long 2016). NDVI calculates the difference between red wavelengths, which is absorbed by chlorophyll, and NIR which is reflected. Red and NIR bands have been used for vegetation monitoring because they are more closely correlated with plant height, density and percent cover (Barnes et al. 2000). As a corn canopy develops from emergence to full growth, NDVI values initially increase, then eventually saturate with further increases in plant biomass. Red reflectance and NIR are inversely related. Healthier and higher biomass vegetation has increasing NIR reflectance but decreasing red reflectance making NDVI sensitive to changes in green biomass until canopy closure. Once the corn canopy has closed, changes in the red wavelength are small compared to the NIR values (Bean et al. 2018; Dias Paiao, 2017; Mulla 2013). Normalized Difference Red Edge index values range from -1 to 1, like similar to NDVI, but NDRE utilizes the sensitivity of the red-edge (RE) reflectance, which has a higher correlation with yield than that of red reflectance. RE shifts marginally to longer wavelengths as leaf chlorophyll content rises (Barnes et al. 2000; Bean et al. 2018; Dias Paiao, 2017; Modica et al. 2020; Mulla 2013).

Optical sensors can capture plant conditions both spatially within the field and temporally at different sensing times to facilitate in-season N application decisions (Bean et al. 2018). A constraint of sensors is the need to have a high nitrogen (High-N) non-limiting area compared to the target area because it can be difficult to detect slight N deficiencies using just absolute VI values (Ransom et al. 2020). A High-N area can be used as a reference to provide relative differences in reflectance values between the reference and different areas of a field. In addition, a high-N area can help account for variations in sunlight conditions between measurement dates which is a problem for passive sensors. Potential changes in illumination conditions are a confounding factor affecting comparison of absolute VI values between sensing dates. It can be avoided by using the relative difference in VI values. The relative difference in VI values should be more comparable between sensing dates because changes in illumination conditions will affect the reflectance from both the area of interest on the field as well as the High-N area reflectance.

2.2.3 Ways to Estimate Growing Season N Addition Using Spectral Reflectance

Oklahoma State University (OSU) was the first to create an in-season spectral reflectance N rate estimate algorithm. The main objective for creating the algorithm was to predict grain yield early in-season so that N fertilizer application decisions could be made early enough to apply in-season N fertilizer in time to overcome N deficiencies. In the OSU algorithm (Lukina et al. 2001), the steps to determine N application rate requires subtracting current predicted yield from the attainable maximum grain yield. The N in grain is then determined by plotting percent grain N as the response variable and grain yield as the explanatory variable resulting in a quadratic response. The coefficient from the quadratic response is incorporated into the predicted grain yield response model giving the predicted N in grain. Next, the predicted N in grain is multiplied by the difference in maximum grain yield and current predicted yield and divided by a N fertilizer efficiency factor. The in-season fertilizer N dressing requirement calculation (Lukina et al. 2001) is shown in equation 2.1 :

$$[(\text{Maximum Potential Yield - Current Yield}) \times \text{N in grain}]/\ \text{N efficiency factor.} \qquad [2.1]$$

where N efficiency factor is 0.7 under ideal conditions

Franzen et al. (2019) also made an active optical sensor in-season algorithm to calculate N requirement for grain corn. The method measures the High-N (target yield) values and compares them to non-reference areas (estimated field yield). The yield difference is multiplied by the percent N in corn grain and divided by a N fertilizer use efficiency factor. The result is the amount of N fertilizer needed to reach the target yield under current estimated field yield conditions (Franzen et al. 2019) (equation 2.2):

$$[(\text{Target Yield - Estimated Field Yield}) \times \text{N in grain}]/\ \text{N efficiency factor} \qquad [2.2]$$

where N in grain is assumed to be 1.25%, N efficiency factor is assumed to be 0.6

The Franzen et al. (2019) method was developed over several years using corn N rates in North Dakota. It assumes no other elemental deficiencies are present as they can cause incorrect N recommendations. When deficient, sulfur artificially inflates N levels (Franzen et al. 2016) while having micronutrient deficiencies can induce crop stress in similar ways to N deficiencies. When Fe, S, Mg and Mn deficiencies are present in corn leaves, chlorophyll content also decreases, similar to that with N deficiency (Sharma and Bali 2017). A commonality among algorithms to predict N requirement, is they are region-specific (Dias Paiao 2017; Barker and Sawyer 2010; Hoffmann et al. 2016). The delta yield (difference in yield between control and area nonlimited by N) has a high correlation with economic optimum N rate (EONR). Janovicek et al. (2021)

conducted N yield response trials and concluded that delta yield N estimates proportionally increase with increasing corn-N price. For sensor-based algorithm to hold true in other regions, the percent N in grain and fertilizer efficiency factor need to be tested and calculated for the region in which they are to be used.

Spectral reflectance sensing can utilize multiple wavebands at the same time. Blackmer et al. (1996) found that reflectance from different wavebands were similarly affected under changing ambient light conditions when they were sensed simultaneously (Blackmer et al. 1996b). Comparisons between indices being sensed using different platforms required a method to normalize the indices along with means to compare the indices on different sensing dates with differing ambient light conditions (Sumner et al. 2021). This research was intended to provide optical sensor recommendations in Manitoba. Vegetation indices (VI), standardized VI (VI_s) and different sensing platforms were compared to determine the best method to create comparable values on different sensing dates. Multiple site-years of N response trials were used to create a regional response model and adjusted for N fertilizer and corn grain prices to determine the optimum N rate to apply.

2.3 Materials and Methods

2.3.1 Site Description and Soil Nutrients

Canopy reflectance and crop measurements were made using nitrogen plot rate trials set up in 2018, 2019, 2020 and 2021 in Manitoba, Canada (Fig. 2.1). Prior to N fertilization, composite soil samples were taken at a 0-15 cm depth and analyzed for nutrient status. Nitrate-N was extracted from a 1:2 ratio of soil and a $CaCl_2$ solution and measured by automated colorimetry. Phosphorus was extracted using the Olsen method, soluble sulfate was extracted using $CaCl_2$ by inductively coupled plasma optical emission spectroscopy (ICP-OES) and exchangeable potassium was extracted using ammonium acetate and measured by the ICP-OES.

The 2018 and 2020 plots were located at 49° 32.0' N, 98° 0 W near Carman, Manitoba, on Gleyed Black Chernozemic soils that are 70% Kronstal series and 30% Reinland series (Michalyna et al. 1988). These soils are developed on moderately to strongly calcareous, deep, stratified, coarse loamy fluvial and lacustrine deposits. Kronstal and Reinland soils are non-eroded, non-stony, and occasionally slightly saline. They have a medium available water holding capacity, medium to high organic matter content, and medium natural fertility (Manitoba Agricultural 2010). In 2018 and 2020 soil nitrate-N was 36 (2018) and 30 kg/ha (2020), soil phosphorus was 13 mg/kg (2018), and 5.2 mg/kg (2020), soluble sulfate was 2.3 mg/kg (2018) and 4 mg/kg (2020), and exchangeable potassium was 140 mg/kg (2018) and 150 mg/kg (2020). The 2019 plot was located at 49° 41' N, 98° 12' W near Haywood, Manitoba, on imperfectly drained Gleyed Regosol soils of the Long Plain series (Michalyna et al. 1988). These soils are developed on weakly to moderately calcareous, deep, uniform, sandy, wind-modified, deltaic deposits and occur in the middle position of gentle slopes on undulating landscapes (Manitoba Agricultural 2010). Nitrate-N was 42 kg/ha, phosphorus was 8.4 mg/kg, soluble sulfate was 7.5 mg/kg and exchangeable potassium, was 54 mg/kg. The 2021 plot was located at 49° 45' N, 98° 22' W near St. Claude, Manitoba on poorly drained Rego Humic Gleysol soils of the Lelant series (Michalyna et al. 1988). These soils are developed on moderately to strongly calcareous, deep, uniform, sandy lacustrine deposits in level to depressional positions of gentle slopes (Manitoba Agricultural 2010). Nitrate-N was 34 kg/ha, phosphorus was 17 mg/kg, soluble sulfate was 16 mg/kg and exchangeable potassium was 150 mg/kg.

Weather stations operated by Manitoba Agriculture were used for daily precipitation patterns throughout the growing seasons (Fig. 2.1). The 2018 and 2020 precipitation were recorded at the Carman weather station that was 5.8 km from the study site. The St. Claude weather station was used for the 2019 study site (9.8 km distance from site) and the 2021 study site (12.6 km distance).

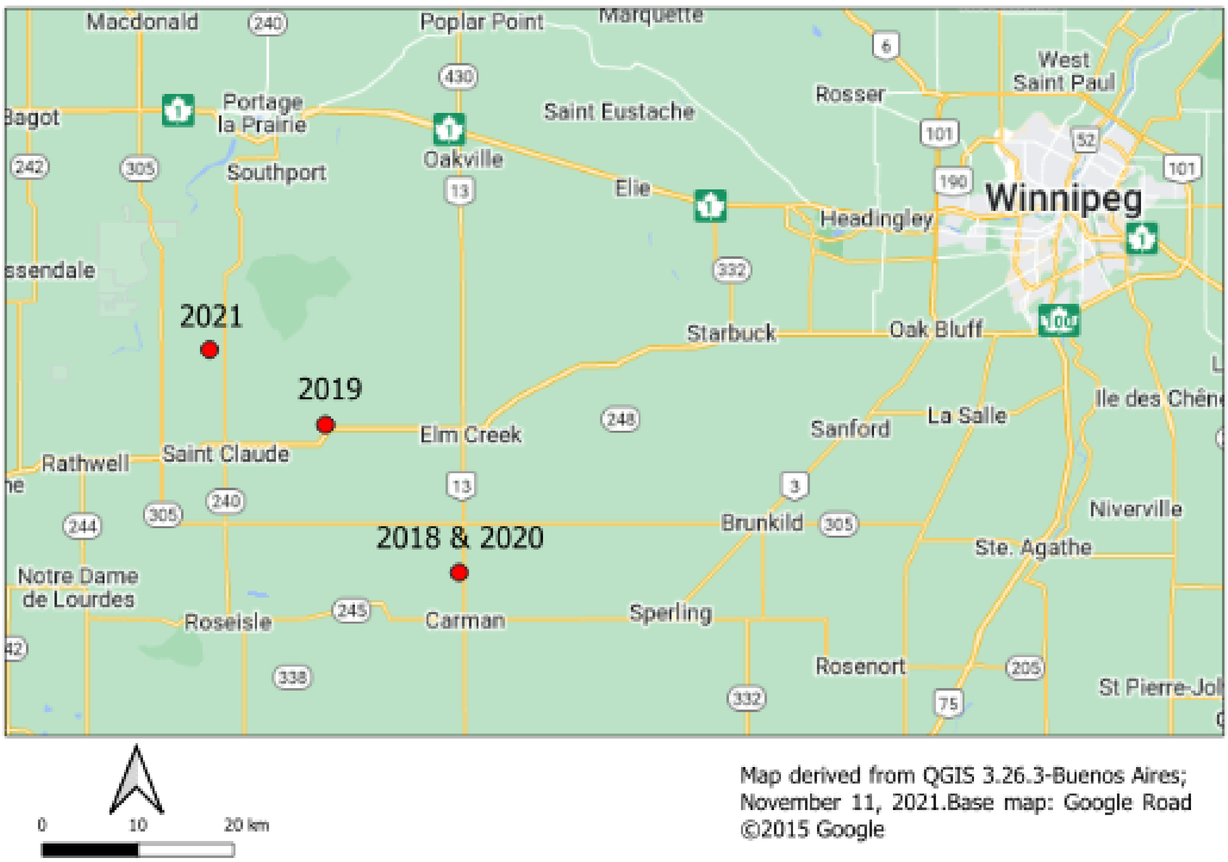


Fig. 2.1 Locations of each field trial where canopy reflectance and crop measurements were conducted in Manitoba, Canada.

2.3.2 Experimental Design and Agronomic Practices

The experiment in each field site consisted of a randomized complete block design (RCBD) with a one-way treatment structure (rate was the single factor) replicated four times (4 blocks total). Grain corn reflectance was evaluate at V4, V8 and V12 stages for different N fertilizer rates using optical sensors to develop the relationship between NDVI, NDRE and yield. Based on the Manitoba Soil Fertility Guide (Manitoba Agriculture 2007) a target yield of 6,725 kg/ha on a field with 34 kg/ha of residual soil nitrate-N would require a fertilizer application rate of 112 kg N/ha. Nitrogen rates each year were based on the recommended rate of 112 N kg/ha used each year to develop the relationship between NDVI, NDRE and yield (Manitoba Agriculture 2007). Each plot had four rows, 8m long by 3m wide. Four N rates (0.5x,0.75x,1x,1.5x recommended rate) were replicated once in each of the four blocks, while an unfertilized check of 0 N appeared twice in each block. Rates ranged from 0 (check) to high (1.5x recommended) and were intended to determine grain corn yield N response and create differences in canopy N status to be detected by the active and passive sensors.

The timing of N fertilizer was split into pre-plant and in-season for all site-years. A control of zero kg/ha N appeared twice in every block. All in-season plots except for the control (no N added) received 35 kg/ha of side-band urea applied at planting. In addition to a zero N control there was an in-season (35 kg/ha applied only at planting) control. All subsequent plots received the remaining to 0.5x,0.75x,1x,1.5x of the recommended rate of 112 N kg/ha applied at the V4 growth stage. The in-season N source was UAN. In-season plots were used to test our MRTN in section 2.4.4

All trials were rainfed and planted with the most common grain corn hybrid used by farmers in the area: Dekalb DK 33-78RIB. This hybrid has a relative maturity rating of 83 and a 2450 corn heat unit (CHU) rating at a target seeding rate of 14,569 to 15,378 seeds/ hectare. Pre-plant N applications of urea (46-0-0) were applied at incremental N rates (0.5x, 0.75x, 1x and 1.5x recommended). Soil ammonium and nitrate testing was done at two depths (0-15 cm and 15-

60 cm) at corn development stages of V4, V8 and V12 and prior to planting (spring) and after harvest (fall). Soil samples were collected from the planting rows by hand, using a dutch auger at mid-row to reduce the risk of including starter fertilizer. Composite samples consisted of five cores (0-15 cm, 15-60 cm) taken during spring sampling. Fall nitrate-N soil samples were collected at each treatment plot, analyzed at the University of Manitoba, Department of Soil Science Laboratory, and measured by automated colorimetry using a Technicon Autoanalyzer II (Technicon Industrial Systems, Tarrytown, NY) system.

To determine soil nitrate-N from a lab analysis, bulk density of the 0-15 cm depths was assumed to be 1.25 Mg/m^3 and for the 15-60 cm it was assumed to be 1.34 Mg/m^3 bulk density, typical of loamy soil. The bulk density x $1000m^3$ x depth in meters provided the soil mass.

The following calculations were done for both spring and fall nitrate-N testing to convert ppm (mg N/g dry soil) to kg N/ha:

Determining the soil mass of a loamy soil from a depth of 0-15 cm and a bulk density of 1.25 Mg/m^3:

$$1.25 \frac{Mg}{m3} x\ 10000 \frac{m2}{ha} x\ 0.15\ m = 1875 \frac{Mg}{ha}$$

The soil nitrate-N was calculated from the total soil mass:

$$\frac{g\ N}{Mg} x\ 1875 \frac{Mg}{ha} /1000 \frac{g}{kg} = \frac{\mathrm{kg\ N}}{\mathrm{ha}}$$

Fertility analysis (Nitrate-N, Olsen-P, NH_4OAc exchangeable K, Ca, Mg, Na; water-extractable S and CL; DTPA-extractable micronutrients; pH; EC and organic matter) of soil samples collected during the spring were submitted to Farmers Edge Laboratories. Before planting, P and K fertilizer was applied to assure N was the only limiting macronutrient.

2.3.3 Grain Yield

The two mid of four total rows were harvested to minimize fertilizer drift effects and to avoid the soil sampling (two outer) rows. Corn plants were counted, cut and collected 1 m from the ends of the harvest rows. Grain cobs were separated from the plant and weighed separately while the corn husk was left with the biomass. Cobs were threshed in the combine, weighed and the grain was collected. Three cob cores and three threshed biomass samples were used separately to create a subsample of each plot. Subsamples of grain and biomass were weighed to determine moisture content. Grain and biomass samples were oven dried at 65-77˚C for 48 hours or until the weight was stable. The dried threshed corn mass divided by the harvest area was converted to a standard 15.5% moisture content basis and represented the standard moisture in this study. The grain and biomass were ground and analyzed for total N.

In 2018 and 2021, corn grain samples were processed at the University of Manitoba, Department of Soil Science lab for total nitrogen using combustion (VarioMax Cube, Elementar Analysensystem GmbH, Hanau, Germany) also using the same model of analyzer. The 2019 and 2020 grain samples were sent to AGVISE™ Laboratories for total nitrogen using dry combustion. Percent N in grain was averaged each year for the pre-plant urea plots and the mean was calculated of all the years.

2.3.4 Fertilizer Grain Use Efficiency

Fertilizer grain use efficiency (FGUE) is the amount of applied fertilizer that was taken up and incorporated into grain (equation 2.3). It is a measure of nitrogen use efficiency that focuses on grain N content (Lollato et al. 2019).

$$\text{Fertilizer Grain Use Efficiency} = \frac{\text{Grain N}}{\text{Supply N}} \qquad [2.3]$$

The FGUE was calculated on a dry basis. The percent N in grain from the control (0 kg/ha) was subtracted from each N rate (56, 84,112 and 168 kg/ha). The difference between the high N and control grain yield was divided by the N rate (equation 2.4). Fertilizer grain use efficiency was calculated using equation 2.4 each year separately and the average across all years was used to make N addition requirement calculations.

$$\text{FGUE} = \frac{\left(\frac{\%\text{ N in Grain x Dry Grain Yield}}{100} - \frac{\%\text{ N in Control x Dry Grain Yield of Control}}{100}\right)}{\text{N Rate}} \qquad [2.4]$$

2.3.5 Optical Sensor Data Collection and Processing

Optical sensor readings were collected around the V4, V8 and V12 stages of corn phenological development (Table 2.1) using three different sensors. The GreenSeeker® (GS, Trimble, Sunnyvale, CA, USA) and CropCircle ACS-470 (Holland Scientific, Lincoln, NE, USA) (Fig. 2.2) are both handheld, active ground-based sensors (GBS). The GreenSeeker® continuously emits brief bursts of light and measures the reflected red (660 nm wavelength) and NIR (774 nm wavelength) radiation then displays NDVI values on the screen (Basyouni 2017; Sharma et al. 2015). The CropCircle$^{\text{TM}}$ used a multicolored LED three-channel light source that measured the reflectance of red (670 nm wavelength), RE (730 nm wavelength) and NIR (760 nm wavelength) (Table 2.2) simultaneously (Sharma et al. 2015). Each active sensor measurement for an individual plot was collected while walking in one direction at a constant speed and holding the sensor above one of the two center rows, then walking back and holding the sensor above the other center row (Fig. 2.2). Measurements were taken in all plots at V8 and for those plots with pre-season urea applied at V4 and V12.

Table 2.1. Location, planting, harvest and sensing dates by corn growth stage at each between 2018 and 2021 in western Canada.

Year	Location	GPS Coordinates	Planting	Harvest	V4	V8	V12
2018	Carman	49° 32.0' N, 98° 0 W	May-23	Oct-30	Jun-21	Jul-09	Jul-23
2019	Haywood	49° 41' N, 98° 12' W	May-09	Oct-24	Jun-28	Jul-15	ND[a]
2020	Carman	49° 32.0' N, 98° 0 W	May-11	Oct-02	Jul-02	Jul-16	Jul-24
2021	St. Claude	49° 45' N, 98° 22' W	May-13	Oct-18	Jun-15	Jul-6	Jul-22

Note: [a]ND-no sensed data for corn vegetative growth stages V4, V8 and V12

Table 2.2 The spectral reflectance data used in this study.

Platforms/Sensor	Index	Sensing Angle	Formula	Reference
GreenSeeker®	NDVI[b]	Oval, 60 cm x 1 cm	$\frac{(774\ nm - 660\ nm)}{(774\ nm + 660\ nm)}$	Sharma et al. 2015
CropCircle™	NDVI	Oval ,32 ° by 6 °	$\frac{(760\ nm - 670\ nm)}{(760\ nm + 670\ nm)}$	Sharma et al. 2015; Cao et al. 2016
CropCircle™	NDRE[c]	Oval, 32 ° by 6 °	$\frac{(760\ nm - 730\ nm)}{(760\ nm + 730\ nm)}$	Sharma et al. 2015; Cao et al. 2016
UAV/MicaSense[a]	NDVI	47.2 ° HFOV	$\frac{(840\ nm - 668\ nm)}{(840\ nm + 668\ nm)}$	Jasim et al. 2020; MicaSense Inc. 2015
UAV/MicaSense	NDRE	47.2 ° HFOV	$\frac{(840\ nm - 717\ nm)}{(840\ nm + 717\ nm)}$	Jasim et al. 2020; MicaSense Inc. 2015

Note: In 2021, an Altum camera was used with a near infra-red wavelength centered on 842 nm, rather than 840 nm with a field of view of 48 °x 37 °
[a]Wavelength values shown are for the Red Edge 3 camera used in 2018, 2019 and 2020 with a field of view of 47.2°; [b]Normalized difference vegetation index; [c]Normalized difference red-edge index

Fig. 2.2 Corn reflectance being measured by the GreenSeeker® (back) and the CropCircle™ (front).

The third sensor was the MicaSense (Seattle, WA, USA), a passive, multi-spectral camera (RE-5) mounted to a quadcopter (DJI, Shenzhen, China) uncrewed aerial vehicle (UAV), (Fig. 2.3). The MicaSense Red Edge 3 (RE-3), a 5-channel camera, was used in 2018-2020. The RE-3 collects reflectance light in blue (475 nm wavelength), green (560 nm wavelength), red (668 nm wavelength), near infra-red (840 nm wavelength) and red edge (717 nm wavelength) wavelengths with an image pixel width of 4.8 mm The ground sampling distance at 120 m is 8cm/pixel. In 2021, a Micasense Altum camera was used to collect reflectance data in the blue (475 nm wavelength), green (560 nm wavelength), red (668 nm wavelength), near infra-red (842 nm wavelength) and red edge (717 nm wavelength) wavelengths with a pixel width of 7.12 mm (MicaSense Inc. 2015; Mullen et al. 2003). The ground sampling distance at 120 m operating the Red Edge 3 was 8cm/pixel compared to 3.98 cm/pixel (MicaSense Inc. 2022). On each measurement date, the canopy reflectance was measured at a sensing height of about 60 m within 2.5 hours of solar noon to ensure full natural sunlight. The camera was programmed to collect images every 1.5 seconds and the UAV was operated on a course with a series of overpasses to acquire images with 70% overlap along-track and on adjacent tracks.

Fig. 2.3 The MicaSense Red Edge 5-channel camera mounted on UAV platform (DJI Matrice 100) flying over the corn plot at Haywood in 2019.

Micasense RE-3 wavelength bands are spatially not aligned (Aslahishahri et al. 2021). Images were processed using Plot Phenix^{TM} (Lafayette, Indiana, USA) by first aligning each band separately on a pixel-to-pixel basis per band and then merging the five camera files for the B, G, R, RE and NIR wavelengths, merging a series of stacked multi-spectral image for each measurement date and location. Image distortion was removed by 3D point matching and reconstruction (orthorectification). Using Plot Phenix^{TM}, the images were then stitched together to create a single geometrically-corrected image (orthomosaic) for each image acquisition date. A standard reference panel was used for spectral calibration for each flight. Treatment plots were gridded on the orthomosaic and only the center two rows per treatment plot were used to extract the mean VI values for each plot. During the processing step in Plot Phenix^{TM} had the option to set a threshold that focused on vegetation pixels. This was done by setting a maximum greenness threshold at ½ or ¼ where the software would analyze pixels inside of the measurement zone using a greyscale image and determine which pixels were green vegetation versus non-vegetation. Both threshold setting tried in this study showed little to no improvement and therefore images were processed using the raw reflectance values on each measurement date.

2.3.6 Standardized Reflectance

To determine if standardized reflectance from a High-N plot would improve the relationship between corn grain yield and optical sensing and better predict N requirement across the four years, light conditions were standardized for each measurement date for both active (GreenSeeker® and CropCircle™) and passive (UAV MicaSense multi-spectral) sensors. Standardizing light conditions for the passive sensor was intended to provide comparable data across multiple site years because reflectance measurements from passive sensors are affected by changes in natural light conditions. It was uncertain if standardization for the active sensor would improve the relationship to corn grain yield as active sensors, equipped with a light source, should encounter minimal variations in measured reflectance as a result of changes in natural light conditions.

An approach was developed for standardizing reflectance that could compare both active and passive sensing. This meant standardizing sensed light conditions regardless of the sensor and in a way that was practical for sensor users.

The equation by Gervais et al. (2019) was modified and standardization was calculated as shown in equations 2.5a and 2.5b:

NDVIs = Current plot (NDVI) + (1- Highest plot NDVI on day of sensing) [2.5a]

NDREs = Current plot (NDRE) + (1- Highest plot NDRE on day of sensing) [2.5b]

The High-N plot VI values used in equations 2.5a and 2.5b provide a simple offset correction with no effect on the variance and thus no effect on classification results. However, it should provide an atmospheric correction for different natural light conditions on different sensing dates (Song et al. 2001). Variations of natural light conditions between sensing dates affect all plots including the High-N plot. Subtraction of a constant (highest plot VI on day of sensing) from all plots to derive the $NDVI_s$ and $NDRE_s$ values provides a comparison of "relative" difference in reflectance between each plot compared to the High-N plot. The changes in natural light conditions between sensing dates will affect the absolute reflectance values measured on the plots but the relative difference in reflectance between a given plot and the High-N reference should be less affected.

2.3.7 Calculating In-Season N Rate Requirement

The work of Oklahoma statue University (OSU) and Franzen et al. (2019) was modified to helped guide N addition recommendations (equation 2.6).

Recommended Nitrogen addition = [(Target Yield - Estimated Field Yield) × N in grain]/ Fertilizer Grain Use Efficiency factor [2.6]

where the target yield and estimated field yields were based on Maximum return to nitrogen (MRTN) using 2022 urea fertilizer and grain prices and standardized using the High-N plot reflectance. The N efficiency factor was changed to a fertilizer grain use efficiency factor because this algorithm is specifically made for the amount of the applied N taken up into the grain of corn, which could be determined more specifically than a NUE factor.

2.3.8 Data Analysis

Statistical analysis was done with Statistical Analysis Software (SAS) University (SAS Institution inc.) and replicated in R software (R Core Team 2020) to generate figures. Analysis of Covariance (ANCOVA) was carried out using the generalized linear mixed model (GLIMMIX) in SAS to determine sensor and stage effects on grain yield, with VI and VI_S as a covariate. Blocks were nested within each site year and considered random. Regression analysis using Proc Regression (Proc Reg) in SAS was conducted to determine the relationship between corn grain yield as the dependent variable and sensing platform at different growth stages using the linear model because that was found to be the most significant. The R software linear mixed model, lme4 package was used to generate regression models. Sensor and stage were modelled as fixed effects and VI and VI_S was the covariate structure. At each growth stage, all possible interactions of stage and sensor were modeled to compare the effects of sensors and VI and VI_S had at each stage on yield. Means were compared using Tukey multiple comparisons procedure at $\alpha = 0.05$. Grain yield response to N supply (spring soil nitrate-N + fertilizer N added) across all site years was generated using Proc Reg.

2.4 Results and Discussion

2.4.1 Site Response to Nitrogen

Corn grain yield increased as a response to N fertilizer (N supply) each site year (Fig. 2.4). There was a typical quadratic response function each site year, however, the amount of yield gained per increment of N was not the same between years. The site years with the highest relationship between corn grain yield and N supply were 2020 (adjusted $R^2 = 0.76$) and 2018 (adjusted $R^2 = 0.70$). These two years had very different end-of-season corn grain yields. The 2018 site had a quadratic response where N supply increased as yield increased and then decreased resulting in the highest rate not having the highest yield. The 2020 site showed a more linear response.

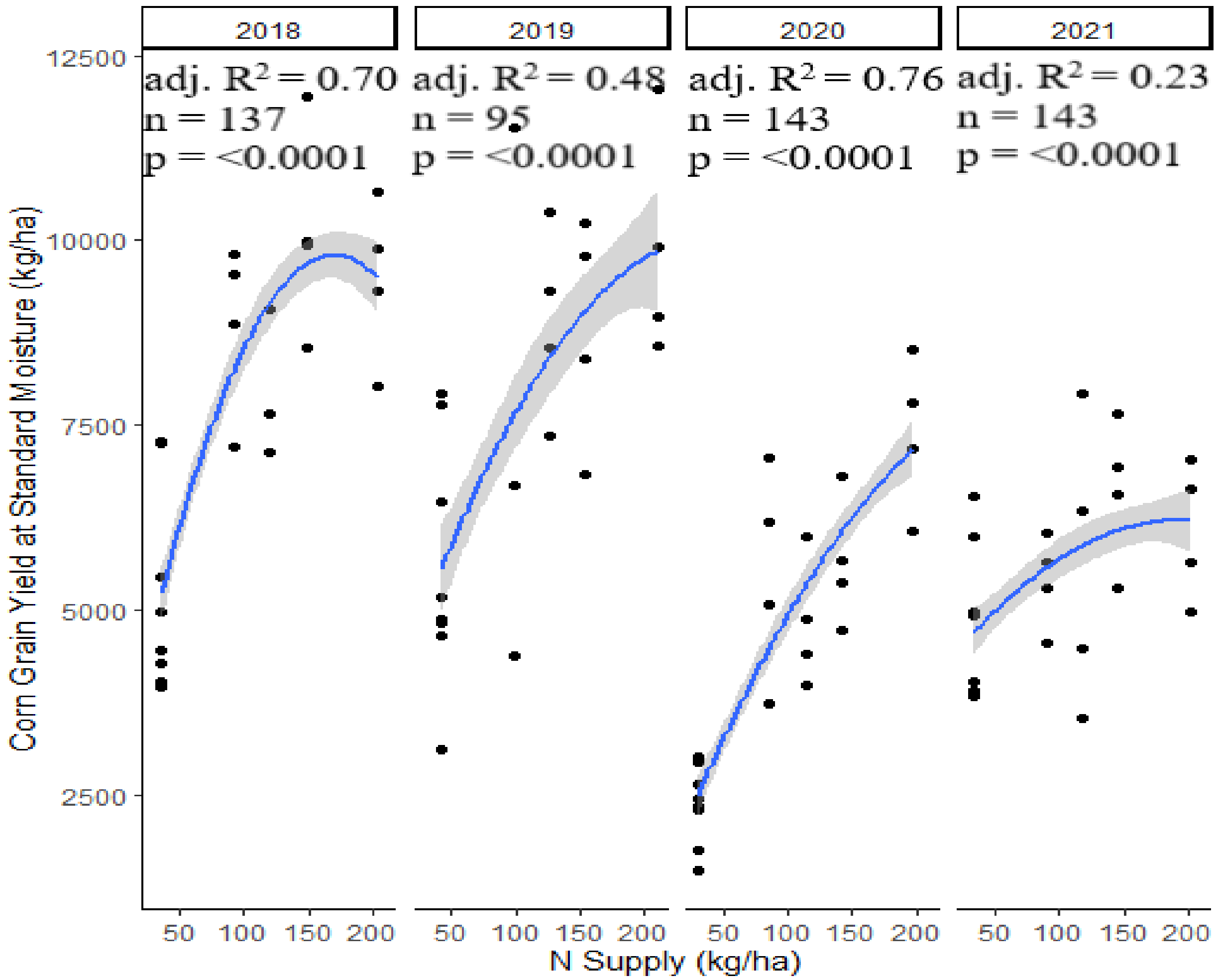


Fig. 2.4 Corn grain yield response to N supply from pre-plant urea addition each site year.

A key contributing factor to the difference in N response was soil moisture. During the four years of data collection, there were differences in precipitation that impacted the amount of soil moisture (Fig. 2.5). Cumulative precipitation from planting to V12 did not differ significantly each year (177-183 mm), however the timing of the rainfall occurrence showed important differences by year. Site year 2018 received 67 mm of precipitation from pre-planting to V4, another 67mm from V4 to V8 and 27 mm from V8 to V12. Precipitation in 2019 accumulated gradually until V8, when a sharp increase occurred. The 2020 and 2021 sites had over 100 mm of precipitation from planting to V4. From V4 to V8, only 46 mm (2020) and 26mm (2021) of precipitation were received. From V8-V12 little measurable precipitation occurred during both years. Although 2021 had ample cumulative precipitation from planting to harvest (394 mm) most of the precipitation came before V8, too early to be translated into high corn grain yield.

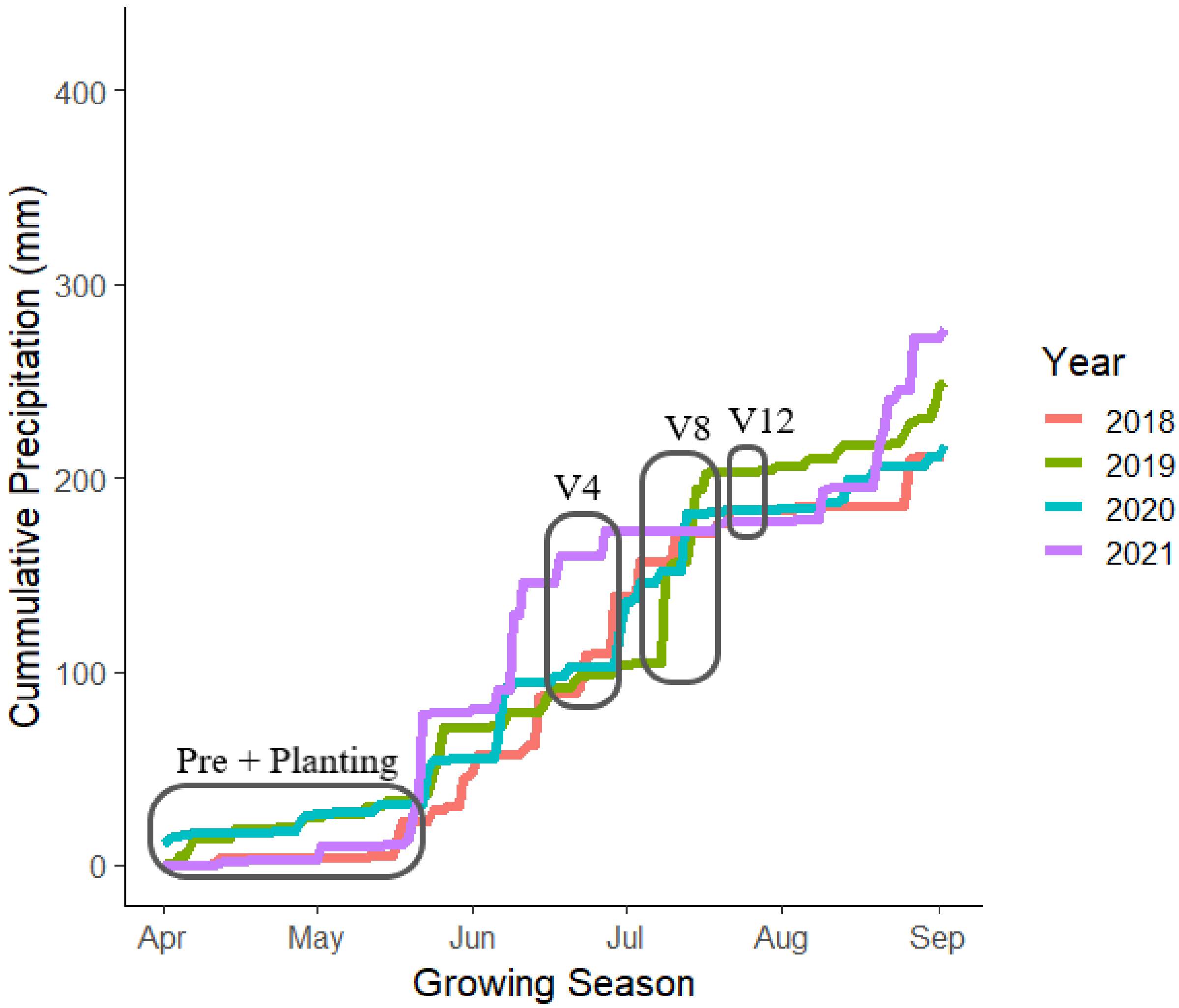


Fig. 2.5 Cumulative growing season precipitation from the nearest Manitoba Agriculture weather stations for each site year with crop stages shown.

By combining 4-site years, a range in growing season precipitation during those years was captured, which is in line with the aim of this thesis research to utilize canopy sensing to improve in-season nitrogen recommendations across different locations in Manitoba. The variation in precipitation and nitrate levels that contributed to different end-of-season corn grain yields, was a benefit to testing this study's methods across a range of conditions. Our study had a typical quadratic response curve across all four site years with grain yield increasing with rising N supply (Fig. 2.6). Thus, our data was able to capture a relationship between end-of-season corn grain yield and N supply across four years using the plots that received pre-plant urea ($_{adj}R^2$=0.40).

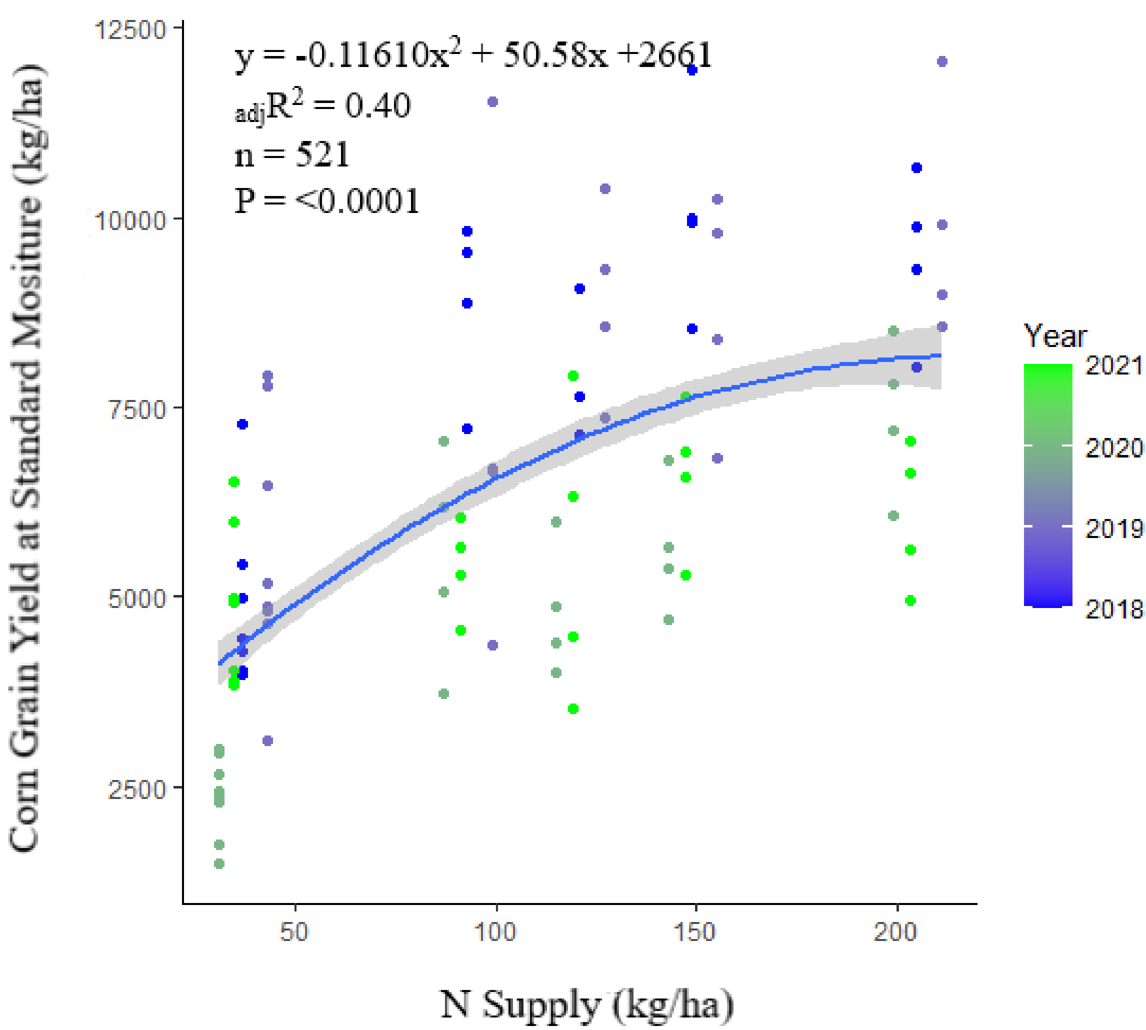


Fig. 2.6 Corn grain yield response to N supply for pre-plant urea addition across study years.

To be able to utilize canopy spectral reflectance to estimate N requirements, the yield response to VI should be similar to the yield response to N supply. In this study, the VI from the plots with pre-plant urea increased with increasing grain corn yield. Thus, we could use VI as a proxy for N supply. Figure 2.7 is an example of yield versus VI using the CropCircle^{TM} NDRE from pre-plant urea plots across all years. The lower values of NDRE and grain corn yield for 2020 and 2021 in comparison with 2018 and 2019 are apparent.

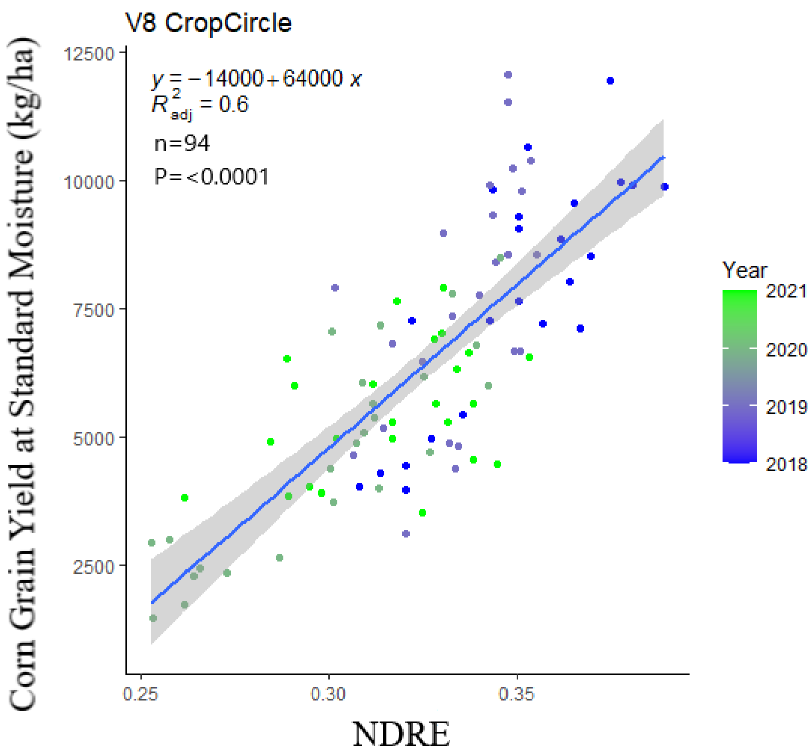


Fig. 2.7 An example of the linear regression trend of corn grain yield response at V8 to the CropCircle^{TM} NDRE on plots with pre-plant urea across study years.

The average spring nitrate-N across all site years was 36 kg/ha (Table 2.3) and varied from 30 kg/ha in 2020 to 42 kg/ha in 2019. Post-harvest nitrate-N levels in 2018 and 2019 were both lower than spring pre-plant nitrate-N, meaning that, on average, the corn utilized more than the applied nitrate-N plus N made available through net mineralization. The highest levels of nitrate-N post-harvest were found in 2020 and 2021 and were higher than the spring nitrate-N levels in both years. In those years, on average, the corn took up less than the nitrate-N applied and made available through net mineralization. Thus, there was an accumulation of soil nitrate-N during the growing season.

Table 2.3 Agronomic information for various nitrogen rate trials conducted in this study using pre-plant urea as the nitrogen source.

Year	Spring NO_3-N Pre-Plant (kg/ha)[a]	Fall NO_3-N Post Harvest (kg/ha)[b]
2018	36	19 (0.6)
2019	42	29 (0.5)
2020	30	35 (1.3)
2021	34	52 (4.9)
Mean	36	34

Note: Values in parenthesis are ± 1 standard error of the mean
[a]Composite samples from five cores (0-15 cm, 15-60 cm) averaged
[b]Automated Colorimetry

The N in grain and Fertilizer Grain Use Efficiency (FGUE) were calculated at the highest N rate of 168 kg N for urea as the nitrogen source each year along with the average across all site years (Table 2.4). The FGUE of urea at the high N rate averaged across all years was 3.0 g/kg. Site years 2018, 2019 and 2020 had the lowest N in grain (12-13 g/kg) and the highest FGUE (3.1- 3.3 g/kg). Although 2020 had more residual post-harvest than pre-plant nitrate-N, it had the second highest FGUE (3.2 g/kg). The limiting factor in 2020 was precipitation which received 60% of the local 30 year average (Table 2.5). The higher FGUE and lower corn grain yield signaled that higher yields under rain fed could not have been reached in 2020. This was the opposite in 2021 which had the highest N in grain of all site years and the lowest FGUE. Precipitation in 2021 was 106% of the local 30 year average, however the timing of the precipitation was mostly prior to V8 and after V12. The corn crop was not able to utilize the nitrate-N leading to standing and high residual post harvest nitrate-N levels. Our sites were all rain-fed and timely rain was important for the corn to take up N. In Manitoba on a typical year, residual N levels range from 28-45 kg/ha (Heard 2022). The importance of knowing residual N levels is to account for total N and reduce fertilizer application rates for the following growing season. The 2021 site had above average residual fall N (52 kg/ha), with pre-plant nitrate-N at 34 kg/ha and the lowest FGUE (2.3 g/kg). The applied N fertilizer was not able to be translated into corn grain yield. Very high residual N levels often occur under drought conditions (Heard 2022).

Table 2.4 Yearly fertilizer grain use efficiency calculated in this study using pre-plant urea as the nitrogen source.

Year	N in grain (g/kg)[a]	Fertilizer Grain Use Efficiency at 168 kg N (g/kg)
2018	12	3.3 (0.02)
2019	12	3.1 (0.05)
2020	13	3.2 (0.05)
2021	15	2.3 (0.06)
Mean	13	3.0

Note: Values in parenthesis are ± 1 standard error of the mean; [a] Dry Combustion (VarioMax Cube, Elementar Analysensystem GmbH, Hanau, Germany)

Table 2.5 Close Proximity weather data for each location, growing season and long-term averages (May 1 – Oct 31)

		Local Monthly Temp (˚C)							Corn Heat Units	
Year	Location	May	June	July	August	September	October	Total	Growing Season Total	% of 30 year mean[a]
2018	Carman	15.5	19.7	20.3	19.3	11.0	3.1	14.8	2828	100
2019	Haywood	10.1	17.4	20.4	18.1	13.1	3.2	13.7	2647	94
2020	Carman	11.1	19.0	20.7	18.8	12.7	2.6	14.2	2894	103
2021	St. Claude	11.0	20.1	22.1	18.6	15.8	8.9	16.1	3201	113
		Local Monthly Precipitation (mm)								
Year	Location	May	June	July	August	September	October	Total	30 year mean	% of mean
2018	Carman	42.5	92.4	44.1	28.0	48.1	36.0	291.1	372	78
2019	Haywood	46.7	31.8	103.3	32.6	152.5	29.7	396.6	372	106
2020	Carman	29.6	69.4	60.0	27.2	17.0	15.8	219.1	372	60
2021	St. Claude	75.9	93.5	5.37	94.8	52.6	73.3	395.5	372	106

Note: [a]Local 30 year mean Corn Heat Units was 2821

Not adding preplant N can induce stress at the V5-V8 stage and reduce yield potential (Holland and Schepers 2010; Bean et al. 2018). At the same time, applying N prior to planting can increase the potential for N losses and lower the potential for N recovery (Paiao et al. 2020). In addition, excess pre-plant N application will delay growth stages. Spring nitrate and timing of precipitation at critical growth stages played a big role in yield differences each year. Often having high residual N could mean that the crop was over fertilized (Flaten and Mangin 2018; Flaten and Gardiner 2019). Plant N uptake is influenced by moisture (Chen et al. 2010). Nitrogen is a mobile nutrient taken up by mass flow (Havlin et al. 2014) thus, having higher moisture leads to higher yield with the same amount of N applied (Manitoba Agriculture 2007). As yield levels increase, so does the demand for nutrients; thus N response varies year to year (Franzen et al. 2016). Crop production is closely linked to meteorological conditions because soil moisture is a critical factor affecting crop biomass production, grain yield and grain quality. The volatility of growing season weather conditions is the biggest contributor to variability in crop production in Manitoba (Nadler and Bullock 2011). Yearly differences in meteorological conditions also lead to varying response to N application (Paiao et al. 2020). This requires the ability to make field scale recommendations that accurately estimate N requirements across years with different precipitation conditions.

The province of Manitoba Soil Fertility Guide (2007) recommends using "usually about 50%" N fertilizer efficiency to develop a fertilizer recommendation rate (John Heard, personal communication). Lory and Scharf (2003) calculated an FGUE of 47% from 193 corn trials in five Midwest U.S states. Lukina et al. (2001) used an expected 0.7 N efficiency factor under ideal conditions for wheat in Oklahoma. Franzen et al. (2019) suggest using a N use efficiency factor of 0.6 for in-soil application like UAN. The suggestion of 0.6 would be under good conditions without losses in surface applied followed by rain or in-soil banded. If, however the N fertilizer is surface applied with no rain an efficiency factor as low as 0.2 could be expected. Trimble created a fertilizer estimation chart for the GreenSeeker® using a NUE of 0.55 and a percent N of 1.3 for dryland corn. Lollato et al. (2019) calculated FGUE of wheat under three long term dryland studies in Oklahoma and found that on average FGUE which they called N recovery was 0.33. This study used a FGUE of 0.3 which is in line with Lollato et al. (2019). A FGUE of 0.3 can be used in southern Manitoba for grain corn under sandy to loamy soils. To my knowledge, this is the second study to have calculated FGUE in corn and the first in Manitoba. A best-guess estimate based on research is common practice (Dave Franzen, personal communication).

Maximum grain yields were attained with N fertilizer applications in a two year study one year due to high residual soil N requiring less N to be applied and less losses due to very high precipitation which impeded maximum yield in the other year (Blackmer et al. 1996a). For our study this means that possibly having had one more site year located in the high residual N 2021 site could have resulted in maximum grain yield. This would only be the case if dry conditions did not prevail and there was adequate precipitation to support high grain yields. Mineralization of soil organic matter is reduced under dry conditions penalizing yield while requiring more N per hectare because there is less soil water to move nitrate-N (Heard 2022).

Lory and Scharf (2003) found that increased yield was attributable solely to increased FGUE and not by additional N from 193 responsive sites. Thus, the biggest yield determinant is FGUE, which is inline with our findings. In our study 2018 and 2020 sites had the highest adjusted R^2 between corn grain yield and N supply and the highest FGUE but resulted in very different corn grain yields. Although 2020 had a much lower yield than 2018 adding more N would not have resulted in higher yields because of low soil moisture making available N immobile. In fact, less N could have been added in 2020 to reach the EONR. The 2021 site had the lowest adjusted R^2 between corn grain yield and N supply and the lowest FGUE.

The two common times to apply N is upfront near seeding or a split near seeding and in-season application. In Manitoba applying N at or near seeding has resulted in the most effective yield-increase. Banding N in the spring compared to in the Fall results in 20% more N efficiency. N supply (spring soil nitrate-N + fertilizer N added) was used to calculate total N because in Manitoba pre-plant spring soil nitrate levels are used to determine N recommendations (Manitoba Agriculture 2007; Heard 2022). Fall soil nitrate-N cannot be used as a replacement for spring soil nitrate-N levels because there is a discrepancy in N efficiency. Spring nitrate and timing of precipitation events at critical growth stages played a big role in yield differences each year (Holland and Schepers 2010; Bean et al. 2018). The amount of soil N that becomes available during the growing season in rainfed fields is highly unpredictable (Sripada et al. 2006), which creates a variable yield response to N rate applied. The relationship between spring wheat grain yield and N supply was found by Flaten and Mangin (2018) in Manitoba to be highly variable across years and not suitable to determine N rate response. Tagarakis et al. (2017) found one site year significantly affected yield and N response due to a severe drought in New York. Solie et al. (2012) cautioned that final N rate recommendations need to be tied to standardized historical data (like percent sufficiency index or High-N areas) and not yield attained that year which is critical in calculating the N demand and making yield predictions.

Unlike Flaten and Mangin (2018) wheat trials and despite having different soil nitrate-N levels pre-plant and post-harvest we were able to see a relatively uniform response to N rate applied pre-planting. Our four years of data were also captured under a range of drought conditions that affected yield similarly to Tagarakis et al. (2017) however, all our site years showed a yield response to N. To relate historical data to yield attained we need to move away from individual yields attained per year and capture multiple site years. This study provided a unique opportunity to capture differences in soil moisture and nitrate-N levels along with a range of yields, which should increase the robustness of the yield response model.

2.4.2 Using Canopy Spectral Reflectance to Predict Corn Grain Yield

An ANCOVA was performed to evaluate the effect of sensed NDVI (covariate), sensor and corn growth stage on end-of-season corn grain yield. Since the GreenSeeker® sensor only provides NDVI, only NDVI was utilized in this phase of the analysis. There was a significant (p = 0.0104) NDVI × Stage × Sensor interaction (Table 2.6). To better understand the three-way interaction, NDVI values from each platform were plotted as the independent variable and corn grain yield as the dependent variable for each developmental stage separately (Fig. 2.8).

Table 2.6 Analysis of covariance (ANCOVA) using corn grain yield as dependent and NDVI, sensor and vegetative growth stage as independent variables (n = 783).

Source of Variation	df	Pr>F[b]
Covariate		
NDVI	1	0.0002*
Fixed Effects		
[a]Sensor	2	0.4175
NDVI × Sensor	2	0.3824
Stage	2	<0.0001*
NDVI × Stage	2	<0.0001*
Stage × Sensor	4	0.0075*
NDVI × Stage × Sensor	4	0.0104*

Note: [a]Sensor corresponds to the sensor type GreenSeeker®, CropCircle™ and UAV; Pr>F[b] is significant at p < 0.05 (*)

At V4, there was no relationship between NDVI and corn grain yield (Fig. 2.8, V4). The NDVI values using the passive platform at the V4 corn growth stage covered a wide range (0-0.75). The lower end of the NDVI values was defined by two serpentine patterns that increase with corn grain yield. The upper end of the passive NDVI values had the same pattern as the active sensors. Both active platforms appeared closely related, with similar scatter plot patterns. The slope of the relationship for all three sensors significantly increased from V4 to V8. Again, both active sensors followed similar scatter plot patterns to that at the V8 stage. However, the GreenSeeker®, had a much higher R^2. The passive platform also had an increase in slope at V12 compared to V8.

A commonality across growth stages was that the passive sensor had the broadest range in NDVI values. The only growth stage with a statistically significant relationship between NDVI and yield for the active sensors was V8, while both the V8 and V12 stages were significant for the passive platform.

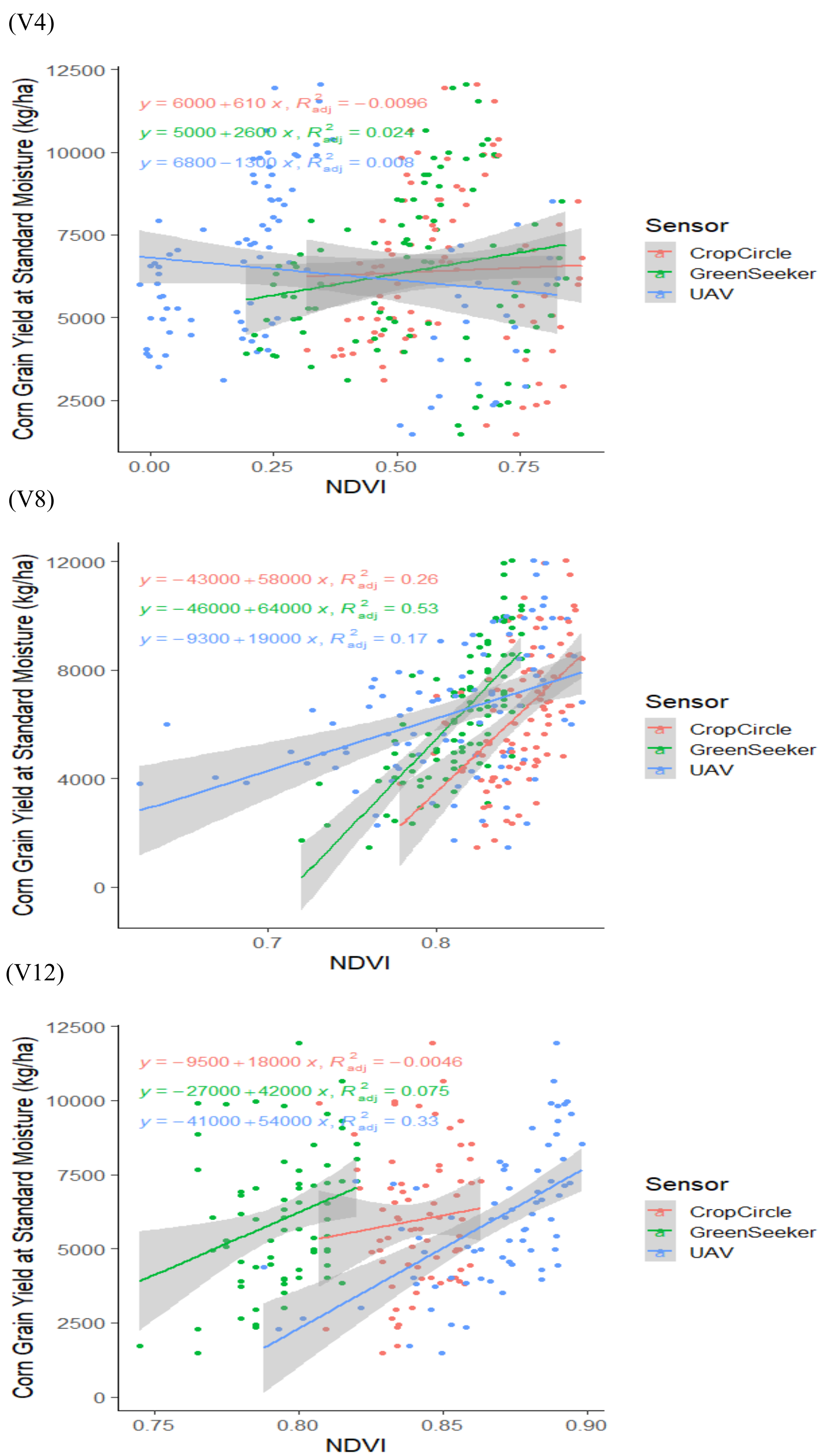


Fig. 2.8 The interaction between sensed NDVI and corn grain yield at each growth stage.

Similarly, the effect of sensed NDRE, sensor and growth stage on end-of-season corn grain yield was evaluated with an ANCOVA (Table 2.6). In this case, the analysis included only the CropCircle™ and UAV, which could provide NDRE values. There was a significant (p = 0.0286) NDRE × Stage × Sensor interaction. The two-way interaction Stage × Sensor was not significant. The three-way interaction was further explored using sensed NDRE from the two sensors plotted as the independent variable and corn grain yield as the dependent variable separately for each developmental stage (Fig. 2.9).

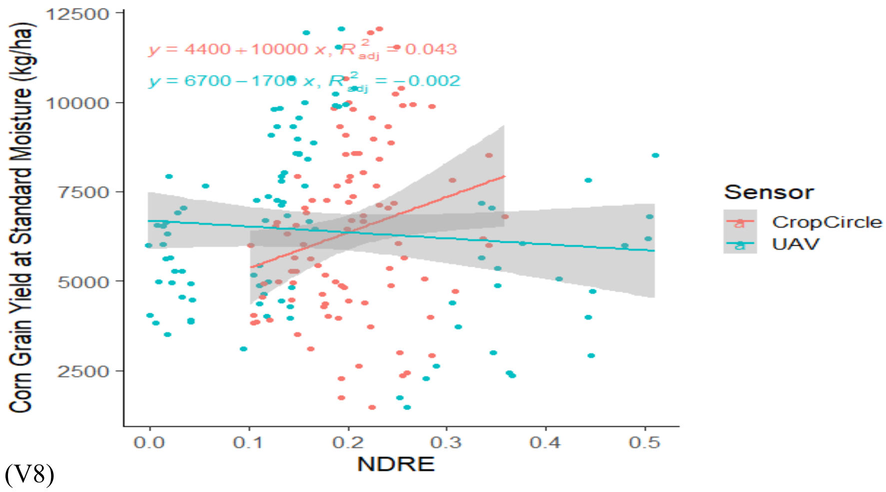
Table 2.7 Analysis of covariance (ANCOVA) using corn grain yield as dependent and NDRE, sensor and vegetative growth stage as independent variables (n = 522).

Source of Variation	df	Pr>F[b]
Covariate		
NDRE	1	<0.0001*
Fixed Effects		
[a]Sensor	1	0.0007*
NDRE × Sensor	1	<0.0001*
Stage	2	<0.0001*
NDRE × Stage	2	<0.0001*
Stage × Sensor	2	0.2212
NDRE × Stage × Sensor	2	0.0286*

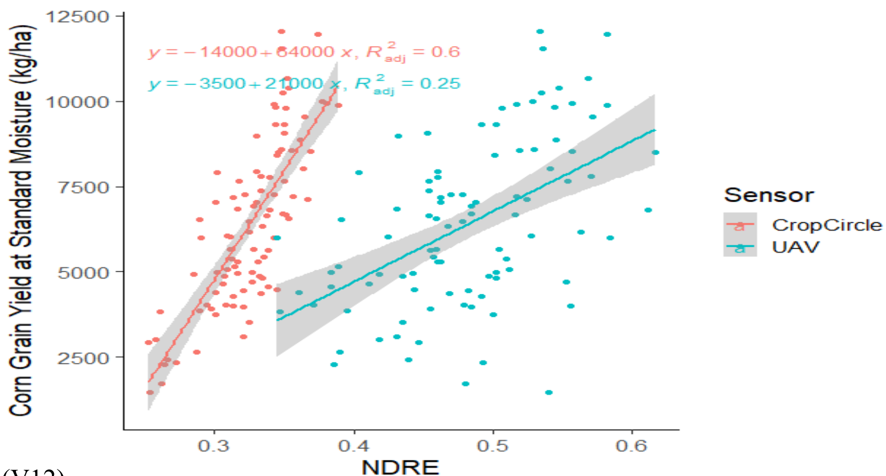
Note: [a]Sensor corresponds to the sensor type, CropCircle™ and UAV; Pr>F[b] is significant at $p < 0.05$ (*)

There was no significant relationship between sensed NDRE at V4, regardless of the platform (Fig. 2.9, V4). The first growth stage at which there was a significant relationship between corn grain yield and canopy spectral reflectance using NDRE was V8. At the V8 and V12 stages, the NDRE from both the active and passive sensors followed the same pattern with NDRE increasing with increased corn grain yield. Both sensors had an increase in slope and higher R^2 from V8 to V12. Although the range in NDRE values did not change with increasing developmental stages, the scatter plot pattern became more clustered and the confidence interval narrower. The significant relationship between corn grain yield and sensed NDRE confirmed the ability to predict corn grain yield using canopy spectral reflectance improved as corn developed. The CropCircle^{TM} had a more consistent change in slope as the corn developed from V4 to V12, making its NDRE values more reliable to predict corn grain yield.

(V4)



(V8)



(V12)

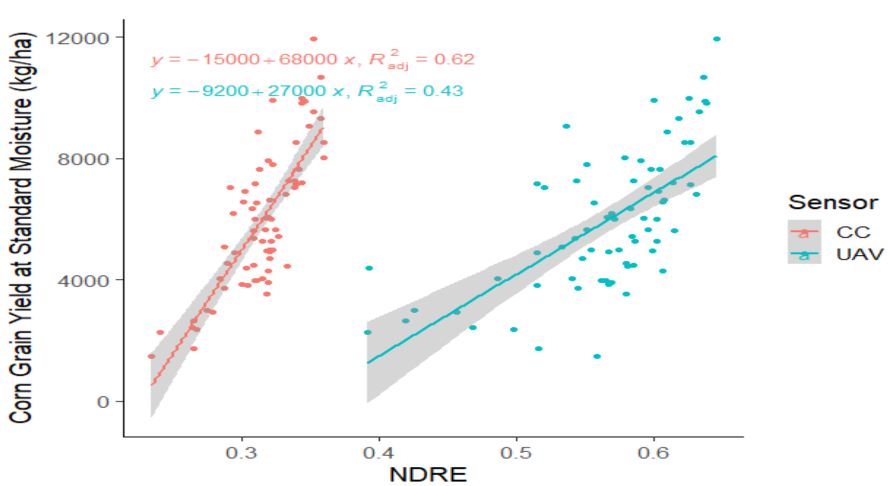


Fig. 2.9 The interaction between sensed NDRE and corn grain yield at each growth stage.

A linear regression model was used to summarize the ability of canopy spectral reflectance sensing NDVI and NDRE at the three growth stages to predict corn grain yield (Table 2.8): At V4, only CC-NDRE showed a significant relationship to corn grain yield but the R^2 value was low. Neither NDVI nor NDRE for any other platform at V4 showed a statistically significant relationship. At V8, both NDVI and NDRE for all sensors had a significant relationship to corn grain yield but the highest R^2 values were for CC-NDRE and GS-NDVI. The UAV-NDVI, UAV-NDRE and CC-NDRE were significant at V12. Across indices and platforms, NDRE at V12 showed the strongest relationship with corn grain yield.

Table 2.8 Linear regression model summary for predicting corn grain yield by growth stage over the four years of this study.

Stage	Platform/Index	Regression Model	Adj. R^2	p
V4	CC-NDVI	y = 6000 + 600x	-0.0095	0.7377
	GS-NDVI	y = 5000 + 2600x	0.024	0.0723
	UAV-NDVI	y = 6800 -1300x	0.008	0.1881
	CC-NDRE	y = 4400 + 10000x	0.043	0.025
	UAV-NDRE	y = 6700 – 1700x	-0.002	0.3688
V8	CC-NDVI	y = -43000 + 58000x	0.26	<0.0001
	GS-NDVI	y = -46000 + 64000x	0.53	<0.0001
	UAV-NDVI	y = -9300 + 19000x	0.17	<0.0001
	CC-NDRE	y = -14000 + 64000x	0.6	<0.0001
	UAV-NDRE	y = -3500 + 21000x	0.25	<0.0001
V12	CC-NDVI	y = -9500 + 18000x	-0.0046	0.4117
	GS-NDVI	y = -27000 + 42000x	0.075	0.0118
	UAV-NDVI	y = -41000 + 54000x	0.33	<0.0001
	CC-NDRE	y = -15000 + 68000x	0.62	<0.0001
	UAV-NDRE	y= -9200 + 27000x	0.43	<0.0001

Note: CropCircle™ is abbreviated as CC, GreenSeeker® is abbreviated as GS

A two year optical sensor study looking at 10 rainfed grain corn growth stages corn in Oklahoma found the strongest relationship between grain yield and VI at the V7-V9 (Martin et al. 2007). The V6 stage was the earliest stage at which a reliable corn grain yield prediction could be made (Sawyer and Randall 2008; Tagarakis and Ketterings 2017). Nitrogen is taken up rapidly after V6 (Schmidt et al. 2009). In the Midwest corn belt region of the United States, N deficiencies did not occur until V7 on rain-fed corn (Bushong et al. 2018). Holland and Schpers (2010) recommend that growers in the corn belt region delay N application until V7 to the silking stage to maximize N synchronization with corn demand. The level of plant growth at V4 may not provide sufficient biomass for differences in N status of the plant tissue to be detected by the sensors. Vegetation indices measured at V4 have resulted in low predictive power (Dias Paiao 2017; Puntel et al. 2018). Schmidt et al. (2011) cautioned that canopy reflectance measurements for corn at V6-V7 are made prior to rapid N uptake and are not capturing variation in corn N demands. The N deficiencies eventually can be detected with reflectance measurements (Freeman et al. 2007) but the crop growth stage at the time of sensing is critical.

Biomass canopy reflectance measurements made early in the growing season are possibly a better proxy to N supply. As the corn crop continues to grow optical sensor measurements become less confined to strictly detecting N supply differences. Sensor comparisons between the Yara N-sensor (similar to the CropCircle™ but is a passive sensor) and the MicaSense Red-Edge supported the finding that NDRE compared to NDVI is not as biomass dependent (Sumner et al. 2021). This was also true in our trials where at later growth stages the relationship between corn grain yield and VI was the strongest, namely CropCircle™ at V12 (R^2=0.62). Although V12 had the highest R^2 which was not extremely high there were other factors that contributed to the relationship between yield and VI, mainly environmental conditions like the corn crop having timely precipitation to be able to take up and use N.

In our trials, growth stage V4 could not predict corn grain yield. The use of NDVI and NDRE at this stage might be too early for the corn crop to have detectable N deficiencies since it precedes the period of high N demand, and the corn may not yet be suffering from lack of N. At

V4, there was no significant relationships for either the active or passive sensors. This is consistent with the notion that at V4, the crop should have enough starter N fertilizer to avoid N stresses and deficiencies to be present. Sensing platforms at this stage are using biomass as a proxy for N supply (Sumner et al. 2021). As the corn canopy develops, indices that were developed to quantify living biomass, such as NDVI (Sulik and Long 2016), are less able to distinguish N supply strictly. Sensing at V8 had the highest predictive power using NDVI. This is in line with Sharma et al. (2015) and Dias Paiao (2017), that the red band becomes saturated at canopy closure meaning NDVI measurements should be used prior to canopy closure and not afterwards (Dias Paiao 2017).

Dias Paiao et al. (2020) found NDRE better at predicting N deficiencies and corn grain yield than NDVI in North Dakota. Sharma et al. (2015) found that sensing NDRE using the CropCircle™ for corn in North Dakota was better at predicting yield at V12. The relationship between VI and N fertilizer using both active and passive platforms had a stronger relationship when using red-edge and a later growth stage (VT) (Sumner et al. 2021). NDRE utilizes RE which has a higher correlation with yield than red reflectance (Bean et al. 2018; Dias Paiao 2017; Mulla 2013). Plants are more reflective in the near-infrared (700-1400 nm) band. The RE and NIR wavelengths display up to 60% reflectance from green leaves in the 700-1300 nm wavelength range. While within the red wavelength, green leaves reflect 20% or less in the 500-700 nm wavelength range (Sharma et al. 2015). The CropCircle™ RE wavelength was 730 nm and the UAV RE wavelength was 717 nm. Thus, the RE wavelength were within the 700-1300 nm range for both sensors and could explain why NDRE was significant at V8 and V12. In our study, NDRE at V12 was the best stage to predict end-of-season corn grain yield. We found the NDRE index was consistently to be a better indicator of grain corn yield than NDVI.

2.4.3 Standardizing Spectral Reflectance Indices Using High Canopy Reflectance Areas to Improve the Estimation of Grain Yield

An ANCOVA was used to determine the influence of standardized $NDVI_s$, stage and sensor on end-of-season corn grain yield. There was a significant ($p = 0.0038$) standardized NDVI × Stage × Sensor interaction (Table 2.9). The ANCOVA for standardized NDVIs behaves similarly to that of NDVI (Table 2.6). The three-way interaction was broken down into sensed $NDVI_s$ from each of the three sensors plotted as the independent variable and corn grain yield as the dependent separately for each developmental stage (Fig. 2.10).

Table 2.9 Analysis of covariance (ANCOVA) using corn grain yield as dependent and $NDVI_s$, sensor and vegetative growth stage as independent variables ($n = 783$).

Source of Variation	df	Pr>F[b]
Covariate		
$NDVI_s$	1	0.0002*
Fixed Effects		
[a]Sensor	2	0.3357
$NDVI_s$ × Sensor	2	0.3272
Stage	2	<0.0001*
$NDVI_s$ × Stage	2	<0.0001*
Stage × Sensor	4	0.0028*
$NDVI_s$ × Stage × Sensor	4	0.0038*

Note: [a]Sensor corresponds to the sensor type GreenSeeker®, CropCircle™ and UAV; Pr>F[b] is significant at $p < 0.05$ (*)

All sensed $NDVI_s$ at V4 was significant and had a positive slope. There was an even distribution of scatter plot points across platforms confirming that standardization improved the relationship between spectral reflectance and corn grain yield at V4 across multiple sensing dates. The active sensor CropCircle™ had the broadest $NDVI_s$ values, ranging from 0.6-1.0. This was the first time that an active sensor had a wider range of VI values than the passive sensor. The slope of the relationship for the two active sensors, $NDVI_s$ versus yield significantly increased from V4 to V8.

At V8, the passive sensor had the broadest range in $NDVI_s$ which has been previously observed for the non-standardized NDVI and NDRE. Progressing from V8 to V12, the slope for both active sensors significantly decreased and the relationship between $NDVI_s$ and corn grain yield was no longer significant. The decline in the relationship between $NDVI_s$ and grain yield response at V12 for the active platforms could not be N related because the passive platform would have been similarly affected. The decrease in slope for both active platforms could possibly be explained by the red wavelength showing only minor changes compared to NIR after canopy closure. The NIR band for the active sensors was 774-760, while the passive sensor had a NIR wavelength centered around 840.

In general, across sensing platforms, the range in $NDVI_s$ values narrowed as the corn developed. The passive sensor was the only one with increasing slope as corn developmental stages progressed. Across platforms, the passive sensor had the most consistent change in slopes throughout the three growth stages but having the most consistent slope was not the best predictor of corn grain yield. The R^2 for the passive sensor did not change but increased slope, indicating that standardization past V4 did not improve the ability to predict corn grain yield. As the corn developed, VI values increased and shifted closer to 1 due to standardizing optical sensor reflectance using the high-N plot. The GreenSeeker® had the strongest relationship to corn grain yield of all sensed $NDVI_s$ platforms at V8.

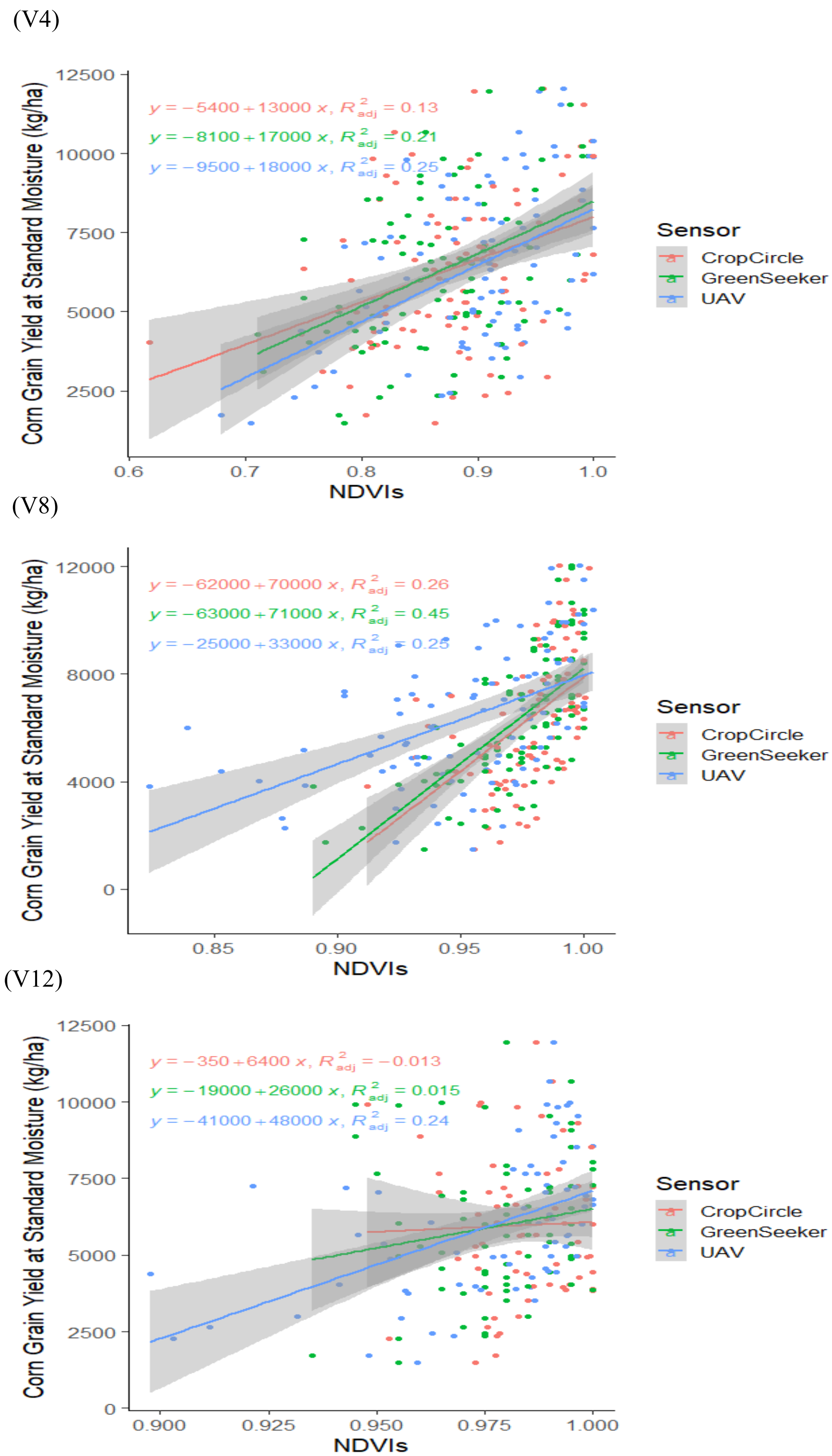


Fig. 2.10 The interaction between sensed $NDVI_s$ and corn grain yield at each growth stage.

An ANCOVA was conducted to determine the effect of sensed $NDRE_s$, platform and growth stage on end-of-season corn grain yield. There was a significant (p = 0.0183) NDREs × Stage × Sensor interaction (Table 2.10). The three-way interaction was partitioned into sensed $NDRE_s$ from each of the three sensors plotted as the independent variable and corn grain yield as the dependent separately for three each developmental stage (Fig. 2.11).

Table 2.10 Analysis of covariance (ANCOVA) using corn grain yield as dependent and $NDRE_s$, sensor and vegetative growth stage as independent variables (n = 522).

Source of Variation	df	$Pr>F^b$
Covariate		
$NDRE_s$	1	<0.0001*
Fixed Effects		
[a]Sensor	1	<0.0001*
$NDRE_s$ × Sensor	1	<0.0001*
Stage	2	0.0006*
$NDRE_s$ × Stage	2	0.0015*
Stage × Sensor	2	0.0087*
$NDRE_s$ × Stage × Sensor	2	0.0183*

Note: [a]Sensor corresponds to the sensor type, CropCircle™ and UAV; $Pr>F^b$ is significant at $p < 0.05$ (*)

Both active and passive sensors had positive slopes and a significant relationship between sensed $NDRE_s$ and corn grain yield at V4. Scatter plots of the passive $NDRE_s$ covered a wider range of $NDRE_s$ values than the active platform. At V8, the slope of the active sensor increased sharply and the range of $NDRE_s$ values became smaller. The passive sensor had a more gradual slope increase and $NDRE_s$ values were more scattered than the active platform.

The relationship between grain corn yield and $NDRE_s$ continued to improve with increasing growth stage for the active platform. At V12, the active sensor's slope and R^2 increased while the passive sensor's slope and R^2 decreased. The relationship between $NDRE_s$ and the corn grain yield for the passive sensor improved up to V8, at which point the R^2

decreased. It was hypothesized that the passive sensor would greatly benefit from standardization because of its sensitivity to variation in natural light conditions between sensing dates, but it was not expected that the relationship would improve for the active sensor as the corn developed due to the platform having its own light source. In fact, it can be misleading to simply see the relationship between $NDRE_S$ values and corn grain yield improve and equate it to the importance of standardizing for light conditions. The relationship between corn grain yield and VI tends to improve as the corn develops. There was an improvement in the reflectance yield relationship by standardizing for changes in light conditions compared to the non-standardized reflectance regardless of the sensing platform at V4.

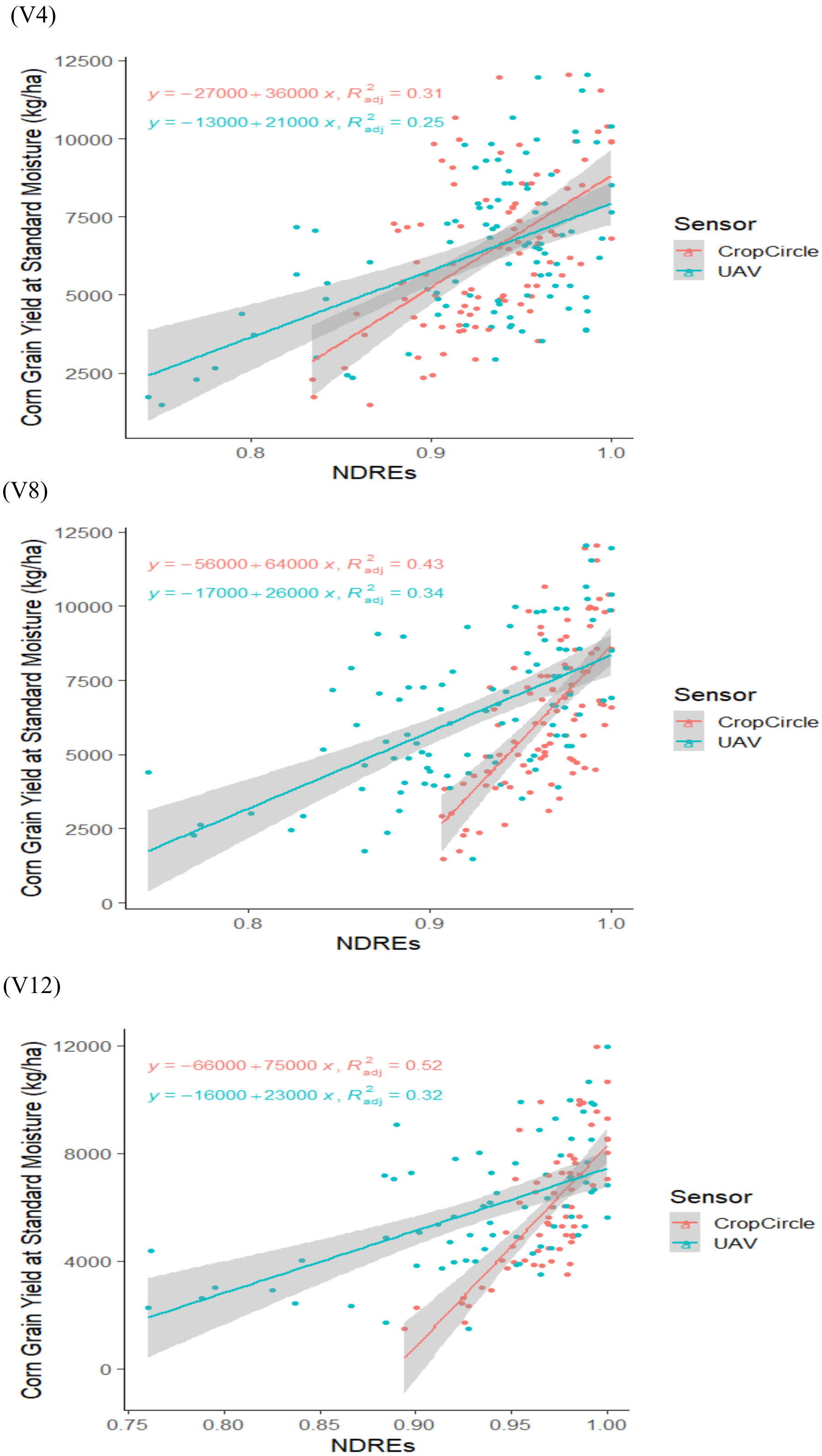


Fig. 2.11 The interaction between sensed $NDRE_s$ and corn grain yield at each growth stage.

A linear regression model was used to summarize the ability of canopy spectral reflectance sensing $NDVI_s$ and $NDRE_s$ at the three growth stages to predict corn grain yield across all four site years (Table 2.11). For all sensing platforms, there was a significant relationship between corn grain yield and VI_S at V4. The strongest relationship when measuring $NDVI_s$ was at V8. The $NDVI_s$ relationship at V12 was not significant for the active sensor. The passive sensor $NDVI_s$ relationship to yield showed no change from V4 to V8 and decreased ability to predict corn grain yield by V12. The $NDRE_S$ relationship to yield was significant at all crop stages regardless of platform. As the growth stage progressed, the ability to predict corn grain yield improved for the active sensor. The passive sensor $NDRE_S$ relationship to yield showed improvement from V4 to V8 but not from V8 to V12. The highest R^2 was the CropCircle™ $NDRE_s$ at V12.

Table 2.11 Linear regression model summary for predicting corn grain yield by growth stages using standardized indices over the four years.

Stage	Platform/Index	Regression Model	Adj. R^2	p
V4	CC-$NDVI_s$	y = -4900 + 13000x	0.12	0.0003
	GS-$NDVI_s$	y = -8100 + 17000x	0.21	<0.0001
	UAV-$NDVI_s$	y = -9500 + 18000x	0.25	<0.0002
	CC-$NDRE_s$	y = -27000 + 36000x	0.31	<0.0001
	UAV-$NDRE_s$	y = -13000 + 21000x	0.25	<0.0001
V8	CC-$NDVI_s$	y = -62000 + 70000x	0.26	<0.0001
	GS-$NDVI_s$	y = -63000 + 71000x	0.45	<0.0001
	UAV-$NDVI_s$	y = -25000 + 33000x	0.25	<0.0001
	CC-$NDRE_s$	y = -56000 + 64000x	0.43	<0.0001
	UAV-$NDRE_s$	y = -17000 + 26000x	0.34	<0.0001
V12	CC-$NDVI_s$	y = -350 + 6400x	-0.013	0.7847
	GS-$NDVI_s$	y = -19000 + 26000x	0.015	0.1571
	UAV-$NDVI_s$	y = -41000 + 48000x	0.24	<0.0001
	CC-$NDRE_s$	y = -66000 + 75000x	0.52	<0.0001
	UAV-$NDRE_s$	y= -16000 + 23000x	0.32	<0.0001

Note: CropCircle™ is abbreviated as CC, GreenSeeker® is abbreviated as GS

Early sensing, regardless of the platform, showed VI measurements clustered by year. Comparing ground and aerial canopy reflectance of corn, Sumner et al. (2021) also found that the greatest variability in VI values was at V4 and decreased as the corn developed. When VI was standardized across platforms, VI_S relationships to yield at V4 were significant.

Most of the vegetation indices that have been developed were intended for remote sensing data from passive sensors on satellite platforms (Rouse et al. 1973; Barker and Sawyer 2010; Jasim et al. 2020). They were created to improve the detection of spectral reflectance of plants while reducing the effects of background soil, light intensity, sun angle and atmospheric conditions (Holzapfel 2007). Popular UAV manufacturers sell downwelling light sources, like the one in this and many studies, to overcome changes in light conditions by making a product to measure and compensate for it. However, in our study the passive sensor mounted to a UAV was not more influenced by changes in light conditions at the time of sensing than the active platforms, specifically at V4 when crop biomass was small.

Spatial resolution refers to the size of the smallest identifiable pixels in a remotely sensed image. The closer the sensor is to the crop, the higher the spatial resolution and the easier it is to distinguish soil versus crop pixels (Messina et al. 2020). Spatial resolution is more relevant at early crop growth stages when the canopy is not fully developed. All active sensor measurements were taken with the sensor less than 1m above the middle two rows. The passive sensor images were acquired using a UAV at approximately 60m AGL. Extraction of the mean plot vegetation index values from the passive sensor was done with Plot Phenix™ which uses an algorithm to focus on the pixels with green vegetation and minize background soil pixels. At early growth stages, the passive sensor has more soil pixels in the images than the active sensors. This is due to a small plant canopy at early stages with more soil background in the passive images, which include the entire plot study footprint versus the active measurements from directly over the canopy, regardless of growth stage. Although the passive sensor images were processed with a focus on plant canopy and eliminating soil pixels, the analysis of the passive sensor data still showed that standardizing for light conditions improved corn grain yield predictions.

Active sensors must take measurements directly over the canopy and require proximity to the sensed target (Thompson and Puntel 2020) because the light source mounted on the sensor has a limited range. An advertised advantage of active sensors is not considering variations in ambient light conditions when sensing (Jasim et al. 2020; Zaeen et al. 2020).

Another stark difference in sensor acquisition between active and passive platforms is the field of view. The three factors influencing active sensor acquisition are its light source, sensing angle and the canopy measurement area. Active sensors come equipped with a light source, so the sensing angle and canopy area need to be considered (Jasim et al. 2020). However, it is generally assumed that following the manufacturer instructions when operating an active sensor will produce accurate results and the light source will not be influenced by ambient light.

Commercial active sensors like the GreenSeeker® use their light source to sense NDVI (Siqueira et al. 2020), an indirect measure of aboveground biomass and nutrient uptake (Holzapfel et al. 2009) to determine N rates by comparing reflectance from a High-N area to other target areas of the field (Siqueira et al. 2020). NDVI is known to be influenced by background factors like shade (Modica et al. 2020) and the brightness of canopy cover and soil background (Modica et al. 2020). Jones et al. (2015) studied the effect of sensing angle had on NDVI readings using the GreenSeeker®. They concluded that different sensor orientations played a minimal role. It was more important to establish multiple High-N reference areas encompassing field variability to help normalize yield and reduce background influences on NDVI (Jones et al. 2015). Our study measured canopy reflectance using both active and aerial UAV while Jones et al. (2015) was focused solely on the GreenSeeker®. Sumner et al. (2021) noticed differences between ground and aerial platforms and suggested that sensor acquisition could be an explanation. The sensing angle on the MicaSense mounted to aerial passive platform is narrower (47.2 ˚ HFOV) than the active platform (32 ˚ by 6 ˚ oval). A narrower sensing angle (that of the passive sensor) results in higher proportion of non-vegetation pixels within each image and thus higher overall non-vegetation pixel footprint than with a broader (active sensor) sensing angle. However, aerial image processing was done to reduce non-vegetation pixels and focus on corn canopy. Our findings did show a difference between active and UAV but that is attributed to the sensing platform and differences in specific bands used by those platforms.

Solie et al. (2012) found linear regression models predicting corn grain yield using spectral reflectance differed greatly by growth stage. They reported VI values response to N fertilizer varied by growth stage, year and sensing platform. This was also true in our study where VI values responded to corn grain yield differently by growth stage, year and platform. Standardizing for light conditions improved the relationship between VI_s and corn grain yield at V4 for both active and aerial UAV despite the close proximity to the canopy and consistent ambient light conditions of the light source for the former.

The later the crop development stage, the smaller was the benefit of standardization played because the difference between the reflectance of the High-N area and the target area was smaller. This is what we experienced. As the canopy developed, the linear regression slope increased due to VI_s approaching 1 with increasing biomass and growth stage. Sensing was standardized using a High-N standard from the highest VI values on the data collection date to assess the differences between plot VI and High-N VI rather than the VI values alone. Thompson and Puntel (2020) found that using a High-N area reduced the influence of background pixels as both the High-N and target area would a similarly background influence, which was true in our study. Gervais et al. (2019) sensed wheat for three consecutive days under three cloud covers (clear sky, thin cloud and heavy cloud). They concluded that sensed VI under different ambient light conditions resulted in an offset in reflectance attributed to the difference in cloud cover. Standardizing the wheat plot reflectance for the three days using a High-N area, overcame the differences as a result of differences in ambient light.

Standardization shifted the VI scale up an amount of 1-the highest reflectance per plot and made VI_S significant at V4. This forced the VI scale to end at 1, decreased the intercept (a, in the linear equation) and increased the slope so that differences in corn grain yield and nitrate-N were not defined as different between years. Standardization of VI_s facilitated the comparisons across different site years, which was not possible previously due to the variation in light conditions between acquisition dates that was especially important at an early corn growth.

V4 does not match the rapid corn N uptake period as it is too early. However, farmers need to make N rate application decisions early in the growing season, which means early in-season, N status needs to be accurately detected. Standardizing both active and passive platforms might be an option to help facilitate early N rate application decisions for growers.

2.4.4 Maximum Return to Nitrogen

A cost-effective way to apply N is to consider the economic component in dollars per hectare of profit from N at specific rates. This is done by calculating the yield increase from applying N at a specific rate, multiplying by the corn price and subtracting the cost of the N. The MRTN is the rate where the return to N is highest (Nafziger 2018). To calculate the MRTN, the price of N fertilizer and corn grain were obtained from Manitoba Agriculture Services Corporation (MASC) and local fertilizer distributors. Work done by Heard (2022) and Gardiner (2022) calculated MRTN for grain corn using 2016-2019 prices which did not reflect the high N fertilizer prices of 2022. Therefore, 2022 fertilizer and grain prices were used to reflect current market conditions at a low, medium and high price ratio (Table 2.12). This study aimed at capturing multiple site years and seasonal variability and wanted to be as representative as possible of current trends and market prices.

Table 2.12 Range in fertilizer and corn grain price ratio typical for Manitoba in recent years.

	Price Ratio		
	Low	Medium	High
Fertilizer \$ kg^{-1} N	\$0.80	\$1.95	\$3.11
Corn \$ kg^{-1}	\$0.15	\$0.25	\$0.34
Price ratio	5.33:1	7.80:1	9.15:1

A common practice is to fit a single yield response model to N fertilizer to understand the relationship between N added and yield. This study showed a typical quadratic yield response curve across all four site years as the N rate increased and grain yield responded (Fig. 2.6). The corn grain yield response to N was calculated using a quadratic model (Cerrato and Blackmer 1990; Stoeckli et al. 2021).

$$Y = a + bX - cX^2 \quad [2.5]$$

Where Y is corn grain yield (kg/ha); X is N supply; a is the intercept; b is the linear coefficient; c is the quadratic coefficient

The derivative of equation 2.5 was used to calculate the MRTN (Stoeckli et al. 2021).

$$MRTN = (\text{Fertilizer to corn price ratio} - b)/\ 2c \quad [2.6]$$

Where b is the linear coefficient; c is the quadratic coefficient from Fig. 2.6

Based on a low, medium and high price ratio, the MRTN values ranged from 177-194 kg N/ha yielding 7,986-8,109 kg N/ha at MRTN (Table 2.13).

Table 2.13 Corn grain yield at Maximum Return to Nitrogen (MRTN) using a range of price ratios for Manitoba across study years and pre-plant urea treatment.

	MRTN	Yield at MRTN	N supply rate to reach MRTN
	kg ha^{-1}		
Low Price Ratio	194	8109	0.0239
Medium Price Ratio	183	8037	0.0228
High Price Ratio	177	7986	0.0222

The N requirement used in this study was estimated based on the current high price ratio $N: $Corn of 9.15:1 and MRTN of 177 kg N/ha for an average yield of 7,986 kg grain/ha.

The corn grain yield response to N supply from Fig. 2.6 can be used to calculate the N requirement for pre-plant urea addition across study years. To understand how corn responds to N applied, the relationship between the control N rate and the high N rate needs to be established (Solie et al. 2012). An MRTN of 7,986 kg/ha was used as the target yield and 4,500 kg/ha as the non-reference estimated field yield. The 4,500 kg/ha was chosen as the estimated field yield because it represented N-limited conditions and could be used for both VI and VI_S. The MRTN of 7,986 kg/ha will henceforth be the target yield and 4,500 kg/ha will be the estimated field yield to remain consistent throughout this study.

The N recommendation to reach the target yield of 7,986 kg N/ha:

1. Using Fig. 2.12, the target yield of 7,986 kg N/ha meets the MRTN at 177 kg/ha
2. The Estimated field yield is 4,500 kg N/ha at 36 kg/ha
3. To reach the target yield, subtract the estimated field yield from the target yield:

   177 – 36 kg/ha = 141 kg/ha N supply

To reach the MRTN corn grain yield at 7,986 kg N/ha under the current estimated field yield a farmer would have to apply 141 kg/ha N.

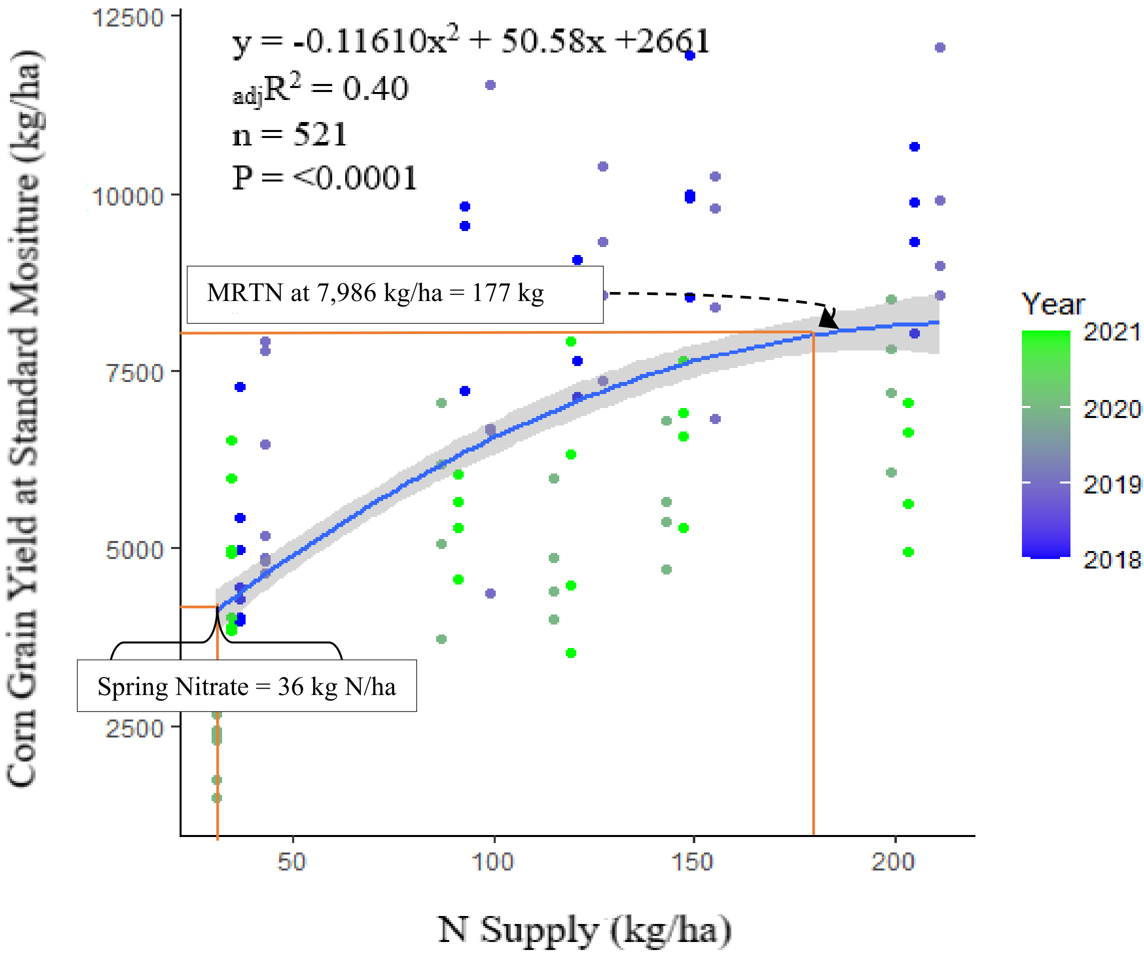


Fig. 2.12 Calculating the N requirement between corn grain yield and N supply (spring soil nitrate plus nitrogen rate).

To test our MRTN, an independent data set of in-season N plots can be found under the methods section. The reflectance of the in-season plots was measured at V4 before in-season N application to assess how well the response curve in Fig. 2.12 could predict end-of-season corn grain yield in-season. Both the pre-plant and in-season plots reflectance at V4 was measured with the UAV only.

To test our MRTN

1. The N supply on each plot was utilized with the quadratic equation in Fig. 2.6 to calculate yield estimate.
2. The estimated yield was subtracted from the actual end-of-season yield.
3. The difference in yield was multiplied by the grain corn price.
4. The fertilizer added on each plot was multiplied by the price of N fertilizer.
5. The difference in yield multiplied by grain corn price was then divided by the amount of fertilizer added, multiplied by fertilizer price.

The Return to N (RTN) showed a successive decline at progressively higher rates of N addition (Fig. 2.13). All plots except the control received 35 kg/ha of pre-plant N. The largest yield increase occurred with the first increment of N addition. Subsequent N additions showed progressively smaller yield increases, which is a typical response. The MRTN occurs at the point where the value of the increased yield is equal to the cost of the N added.

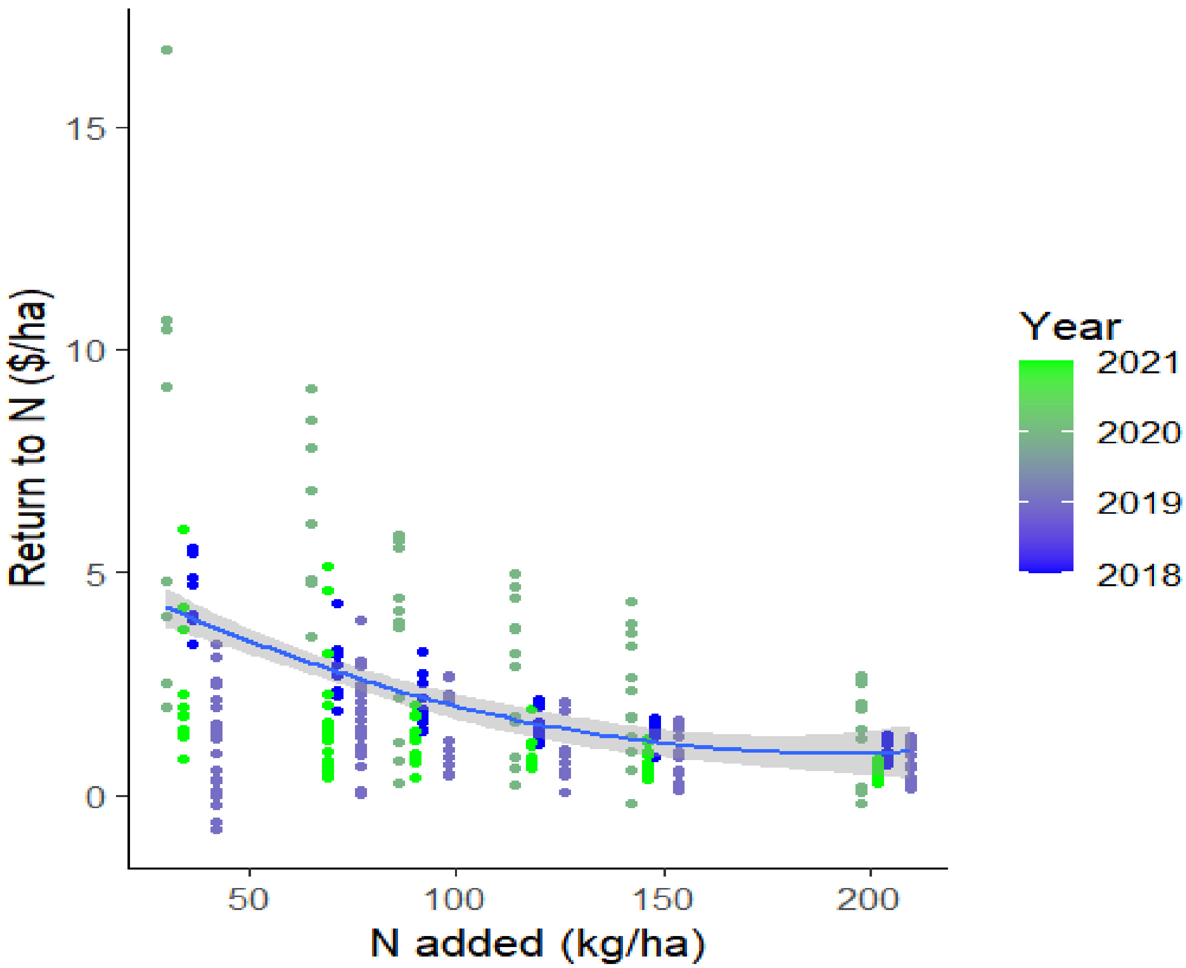


Fig. 2.13 The relationship between return to N and N added.

Corn yield response to N is an important aspect affecting profitability in producing corn because it affects the economics of N fertilizer addition. Fitting a response curve to N fertilizer rates requires yield data at several different N rates. Nitrogen management decisions based on this response is increasingly important as trends in N fertilizer prices increase (Cerrato and Blackmer 1990). Cerrato and Blackmer (1990) conducted multiple years of corn N rate trials (10 rates, 0-336 kg N/ha) and explored different models to describe the relationship between N rate and grain yield. The quadratic-plus-plateau model was the best fit. The quadratic model did not fit their data and, like the quadratic-plus-plateau, it tends to overestimate the most economic optimum point. An advantage of using a quadratic function is that producers want to obtain close to maximum yield with the least amount of N fertilizer. The problem arises that sensors cannot quantify N excess in crops. A popular solution is to use a High-N reference and a control (0 N) where N is low or deficient at the time of sensing (Franzen et al. 2016). Cerrato and Blackmer (1990), Bean et al. (2018) Dias Paiao (2017), Gardiner (2022) used a control (0 N) with at least five N-rate ramp-ups with 225-515 kg N/ha as the highest N rate for corn. There were four N-rates, with 168 kg N/ha as the highest rate in our study. We could not use a quadratic-plus-plateau model because maximum yield was not attained with our highest N rates.

Another approach for determining the most economic rate of N fertilizer is sensor-based. Reflectance can be used as an indicator of crop N status by comparing reflectance from all areas in a field to reflectance from an area with non-limited N. Multidisciplinary academic research using sensors and algorithms to predict N requirement has been done by Sripada et al. 2006; Holzapfel et al. 2009; Baral and Adhikari 2015; Franzen et al. 2016, 2019; Bean et al. 2018. Some common components in these studies of in-season N application using canopy reflectance include the need for a High-N reference strip, the normalization of reflectance measurements and developing in-season N rate algorithms.

2.4.5 Using Spectral Reflectance Indices to Estimate In-Season Nitrogen Dressing of Grain Corn

In our study, spectral reflectance indices were standardized to determine if early vegetation growth could estimate in-season nitrogen status and predict the yield of grain corn. Corn grain yield increased with increasing VI and VI_S which was similar to that of the response of corn grain yield to N supply (Fig. 2.12). These similarities in N rate and sensed VI and VI_s

values to yield response allowed us to estimate the N requirement by applying the nitrogen addition equation 2.6.

A test of canopy spectral reflectance as a basis for N addition is shown in figure 2.14. The UAV $NDRE_s$ at V4 was measured for all the in-season N plots and the regression equation from Table 2.11 was utilized to predict yield. Using a multi-spectral passive sensor mounted to a UAV to sense corn at V4, the yield difference between the target (High-N) and estimated field yield was 3,486 kg corn per hectare compared to no N applied. The percent N in grain averaged across all years was 1.3% which was multiplied by 3,486 kg/ha resulting in 45.32 kg N per hectare. Finally, the efficiency of applied fertilizer to reach the grain (fertilizer grain use efficiency; FGUE) was divided by 45 kg N /ha. Our data used an FGUE factor of 0.3 for pre-plant urea at the high rate of 168 kg N. The 45 kg/ha N deficit divided by 0.3 efficiency factor is 151 kg N/ha. The N supply is added resulting in 187 kg of N per hectare required to reach MRTN at 7,986 kg/ha under the estimated field yield of 4,500 kg N/ha.

Optical sensor algorithm:

1. Determine the yield difference between the target yield and the estimated field yield

   7,986 - 4,500 kg/ha = 3,486 kg/ha

2. Multiply the percent N in grain by the yield difference in step 1.

   3,486 kg/ha x 0.013 = 45.32

3. Divide step 2 by the FGUE

   45.3/0.3 = 151 kg N/ha

4. N to add in season

151 kg N/ha + 36 N supply = 187 kg of N per hectare required to reach MRTN

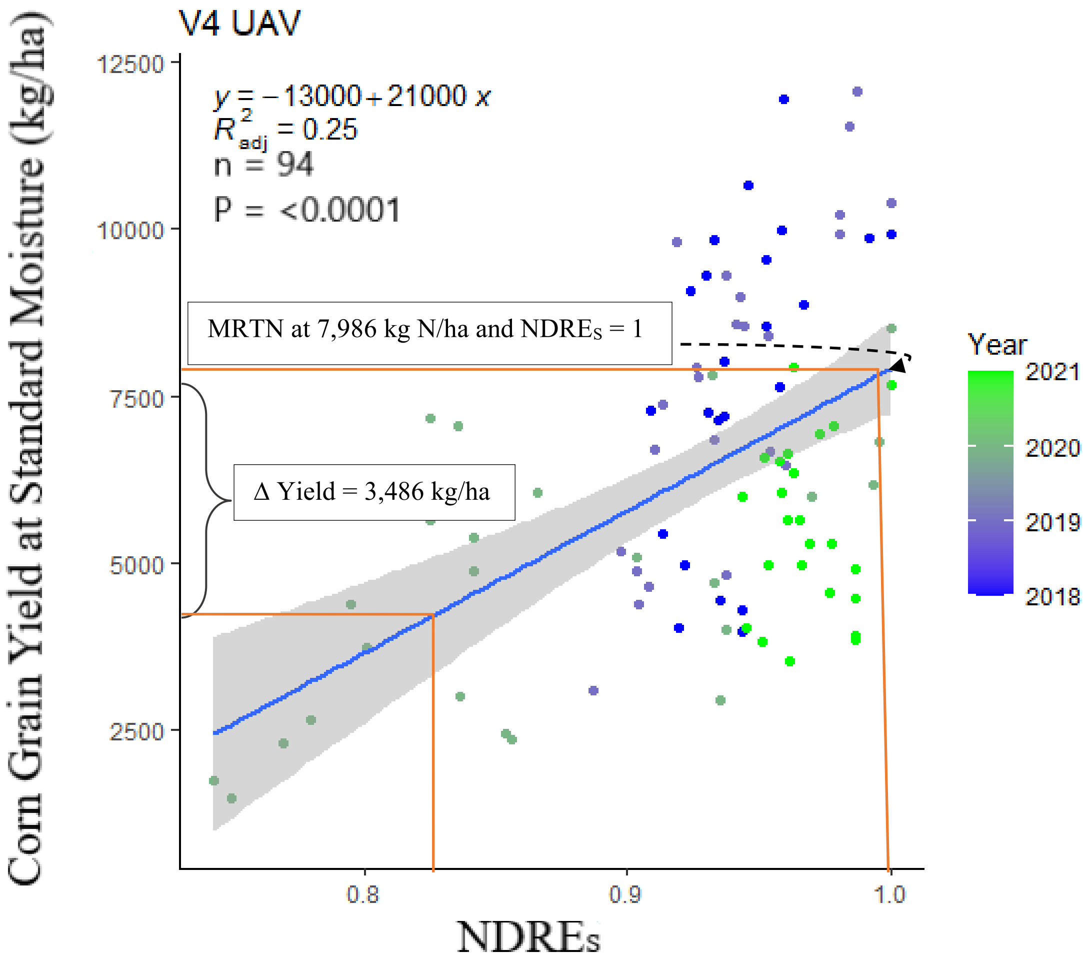


Fig. 2.14 Estimating N requirement from standardized canopy spectral reflectance sensed by UAV at V4 using the MRTN at 7,986kg/ha and a sensed yield of 4,500 kg/ha.

2.5 Conclusion

This thesis provides a basis to use optical spectral reflectance to predict corn grain yield and achieve a maximum economic return to nitrogen in Manitoba. Soil moisture differed during the four site years due to differences in precipitation. For each site year, as corn grain yield increased, the response to N fertilizer did too. However, the amount of yield gained per increment of N was not the same between years. The four site years were combined to capture the relationship between corn grain yield response and N supply under different growing season soil moisture levels which had a significant response to N fertilizer applied ($_{adj}R^2$=0.40).

The first objective of this study was to determine if canopy spectral reflectance during early vegetative growth stages could predict corn grain yield. Canopy spectral reflectance was able to predict corn grain yield at V8 and V12 but not V4. The active GBS CropCircle™ utilizing NDRE at growth stage V8 ($_{adj}R^2$ = 0.6) and V12 ($_{adj}R^2$ = 0.62) was the best sensor/platform for predicting corn grain yield in Manitoba.

The second objective was to determine if standardizing spectral reflectance indices using high canopy reflectance areas improved the estimation of grain yield. Standardizing reflectance values between measurement dates using a high reflectance area resulted in improved grain corn predictions at earlier growth stages for both NDVI and NDRE across platforms. At V4, standardized NDVI had a significant relationship to grain corn yield for both active and passive platforms compared to non-standardized NDVI reflectance. At V8, passive standardized NDVI reflectance improved the relationship to grain corn yield compared to the non-standardized NDVI. At V12, the standardized NDVI relationship to grain corn yield was poorer than at V8. Similarly, for NDRE, the relationship to grain corn yield improved using standardized data at V4 for both active and passive sensors but only for the passive sensor at V8 and for neither sensor at V12.

The last objective was to determine if standardizing spectral reflectance indices captured in early vegetation growth could estimate in-season nitrogen requirement of grain corn. The relationship between corn grain yield and N supply was used to predict the MRTN application rates for corn grown in Manitoba. Under the high \$N: \$Corn price ratio of 9.15:1 and MRTN of 177 kg N/ha was required to reach an average yield of 7,986 kg grain/ha. There were two methods used to make N addition recommendations. The first was using the relationship between N supply and corn grain yield response setting a target yield (MRTN at 7,986kg/ha) and calculating how much N needed to be applied to reach the target yield under the current estimated yield (4,500 kg N/ha). The second approach was estimating N requirement from standardized canopy spectral reflectance using the MRTN at 7,986kg/ha and a sensed yield of 4,500 kg/ha. There was a 46 kg of N per hectar difference between the target approach (141 kg/ha N) and the optical sensor approach (187 kg/ha N). The optical sensor algorithm in this study followed Manitoba corn growing conventions and was on a sandy to loamy soils. If the algorithm is to be used in corn production the above conventions should be followed.

Our study has provided options to use canopy sensors to help make N fertilizer application decisions and predict end-of-season corn yield for corn growers in Manitoba. By combining four site years, we were able to capture N response under different meteorological conditions in Manitoba.

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Overall Synthesis

3.1 Important Research Findings

This study provides Manitoba corn growers with values for local fertilizer grain use efficiency (FGUE) and percent N in grain. When making sensor-based N predictions, the N efficiency or in our case FGUE factor has a significant impact on estimating kg N per hectare required. Nitrogen use efficiency (NUE) is assumed to be around 50%. A higher efficiency means that more of the applied N remained in the grain. Changing only the FGUE to 50% in the optical sensor algorithm means that 91 kg N/ha is needed to reach the target yield, not 141 kg N/ha under a 30% FGUE. Having local crop specific NUE values is important. Using four years of N trial data we found FGUE to be 30% in western Manitoba. Utilizing the optical sensor algorithm allows growers to input their own N efficiency and percent N in grain if they know those values.

Combining sites across years with different growing season moisture conditions provided insight into the variation of crop yield response to fertilizer N with differences in soil moisture which had a significant response (${}_{adj}R^2$=0.40) to N fertilizer applied. The unpredictability of growing season meteorological conditions leads to uncertainty and variability in N management. Applying N during the current growing season based on combined site years, could help reduce uncertainty due to soil moisture and its effect on N.

It is usually assumed that because an active sensor has its own light source it will not be influenced by changes in light condition. The approach of using a high reflectance area to account for variations in light conditions between measurement dates has not been previously done for active or passive sensors. Standardizing spectral reflectance facilitated the comparison across multiple site years, especially at V4, which was not previously possible due to differences in light conditions between acquisition dates. Standardizing VI values shows promise for both active and passive sensors to capture differences in meteorological conditions and make utilizing multiple site years possible.

The vegetation index with the strongest relationship to grain corn yield in our study was NDRE when measured at the V12 ($_{adj.}R^2$=0.62) followed by V8 ($_{adj.}R^2$=0.60) using the CropCircle™. If growers want to use NDVI, the best corn developmental stage is V8 using the GreenSeeker® ($_{adj.}R^2$=0.53).

3.2 Unexpected Findings

Farmers growing the same seed variety in the municipalities where our sites were located (Dufferin and Grey), the average grain corn yield was 9,617 kg/ha in 2018 to 2022 (MASC 2022). In western Canada, using the seed variety used in this study (DKC33-37RIB) seed vendor in 2021 averaged 9,361 kg/ha at 21.7% moisture (Bayer Crop Science n.d). In our study, average yield was lower than the local farmer grain corn yields during any of the four site years. Our highest yielding years were 2018 (8,001 kg N/ha) and 2019 (8,349 kg N/ha) using urea as the N source. Local farmers under similar growing conditions averaged much higher corn grain yields than we did. However, our N recommendations were based on a target yield of 6,725 kg/ha. Although the Manitoba Soil Fertility Guide did have target yield up to 8,743 kg/ha, Flaten and Gardiner (2019) noted that target yields that high were not widespread in Manitoba and would require 218 kg N/ha. Our sites are also not run by farmers but technicians and students. In 2021 the surrounding farmers field within where our site was located was superior to our corn plots. The impact of the knowledge and crop husbandry of farmers was noticeable.

It was surprising the time and knowledge required to take optical spectral reflectance measurements and interpret the data. Learning to operate a sensing platform, especially the UAV, was more difficult than expected and required hours of practise and a pilot's license. A lot of time was spend looking for and learning to use photogrammetry software that could do what was needed in this study. Purchasing photogrammetry software is expensive and required a fast-processing computer.

The biggest surprise was that standardizing active reflectance measurements improved the relationship to corn grain yield. It was thought that since active sensors have their own light source, standardizing reflectance using a High-N area would not be beneficial in reducing the variation of natural light conditions between sensing dates. The relationship between corn grain yield and standardized active reflectance improved only at V4. Previously active and passive sensing at V4 was defined by year and spanned a wide range. What standardization did was shift the scale up 1 minus the highest reflectance per plot forcing the scale to end at 1 and giving early sensing a more comparable range.

3.3 Research Needs for Canopy Sensing to be Used by Growers

This research is a great start to making N dressing recommendation for grain corn in Manitoba. A focus should be on improving FGUE because that has been known to have a greater impact on yield than simply adding more N fertilizer. We did not have a quadratic-plus-plateau model or reach the farmer average yields in the area.

Taking optical reflectance measurements after in-season N application is needed. In-season N was applied after V4 sensing and reflectance measurements were not taken again until V8 (whole field) and V12 pre-plant only. Ideally in-season N side dress should be applied at V8 and canopy spectral reflectance measurements should be taken after in-season N application. V8 is the start of the most rapid N uptake in Manitoba and thus an important stage to sense. This provides the opportunity to predict corn grain yield early but with more biomass than at V4.

The MRTN in this study was 177 kg N/ha to reach a yield of 7,986 kg/ha. The model is only valid when the relationship between corn grain yield and N supply and VI have a yield below 9,000 kg/ha. This might be seen as a limitation for Manitoba farmers who would like to obtain higher yields. Nitrogen was applied all upfront and that could have led to the low FGUE. The MRTN price ratios for Manitoba were based on 2022 corn and urea N prices. The range between the low, medium and high price ratio was between 177 and 194 kg total N supply ha-1 at mean MRTN across four site years. Fertilizer prices ranged from 80 cents kg-1 to 3 dollars and 11 cents with the price of corn ranging from 15 cents to 34 cents kg-1. Our study used N supply which accounts for pre-plant soil nitrate-N and should be subtracted from the MRTN to determine the optimum N fertilizer rate. Future studies should have higher target yields and include more N sources.

At the time this work was started, the downwelling light sensor (DLS) camera on the UAV had technical issues. With in the last two years, Pix4D Mapper (a photogrammetry software), can use metadata saved in each TIFF image about the ambient light and sun angle data recorded from the DLS that was calibrated prior to the flight and captured by the camera. Post processing DLS data has now become very intuitive.As a result of technical issues in the first 2 years the UAV flights for this research were flown without using the DLS. Comparing camera only files that were standardized for changes in ambient light condition with DLS data should be explored.

This research shows a snapshot of 2018-2021 corn grown in western Manitoba. It is my hope that the framework for how to estimate N requirement using optical spectral reflectance of predicted corn grain yield can be easily followed in a way that is beneficial to corn growers.

3.4 References

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Appendices

Appendix A-Estimating N requirement from canopy spectral reflectance presented in Chapter 2

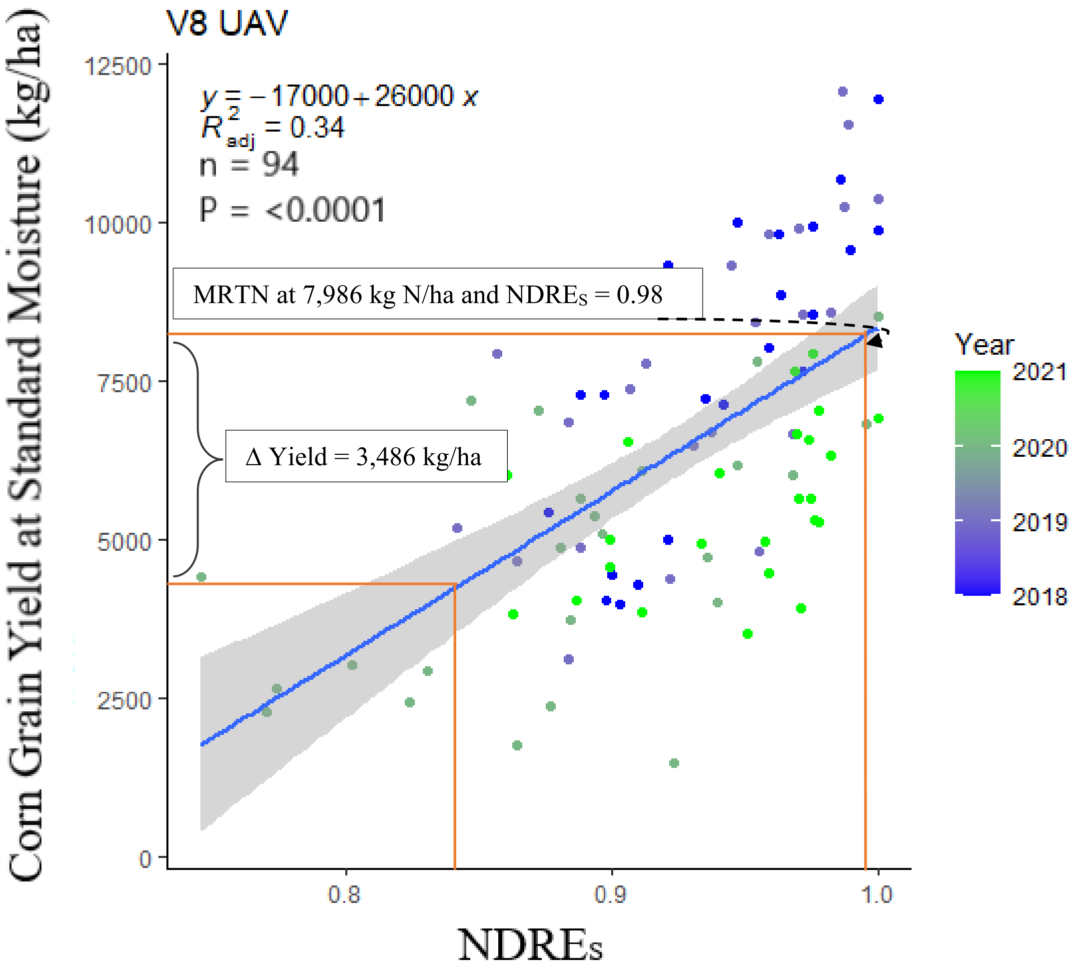

Figure A.1. Estimating N requirement from standarized canopy spectral reflectance sensed by UAV at V8 using the MRTN at 7,986 kg/ha and a sensed yield of 4,500 kg/ha.

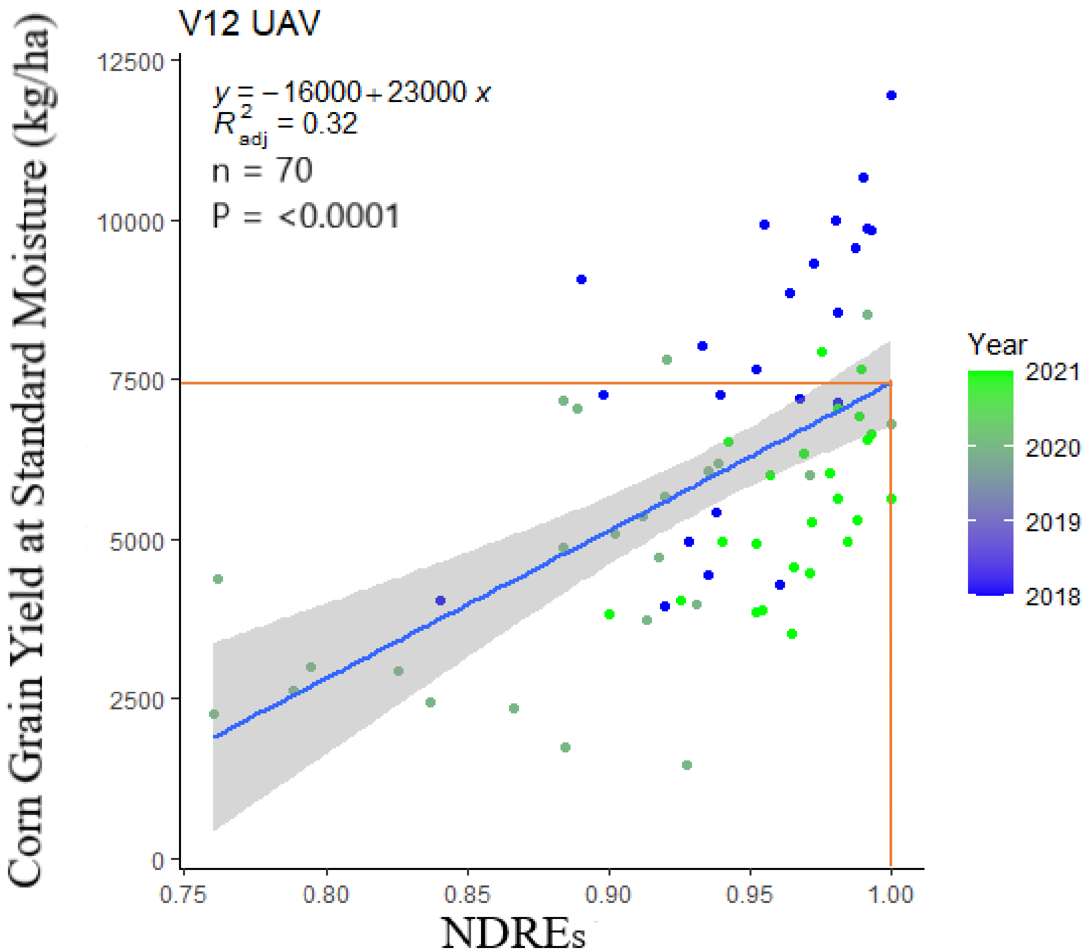

Figure A.2. Estimating N requirement from standarized canopy spectral reflectance sensed by UAV at V12 using the MRTN at 7,986 kg/ha and a sensed yield of 4,500 kg/ha.

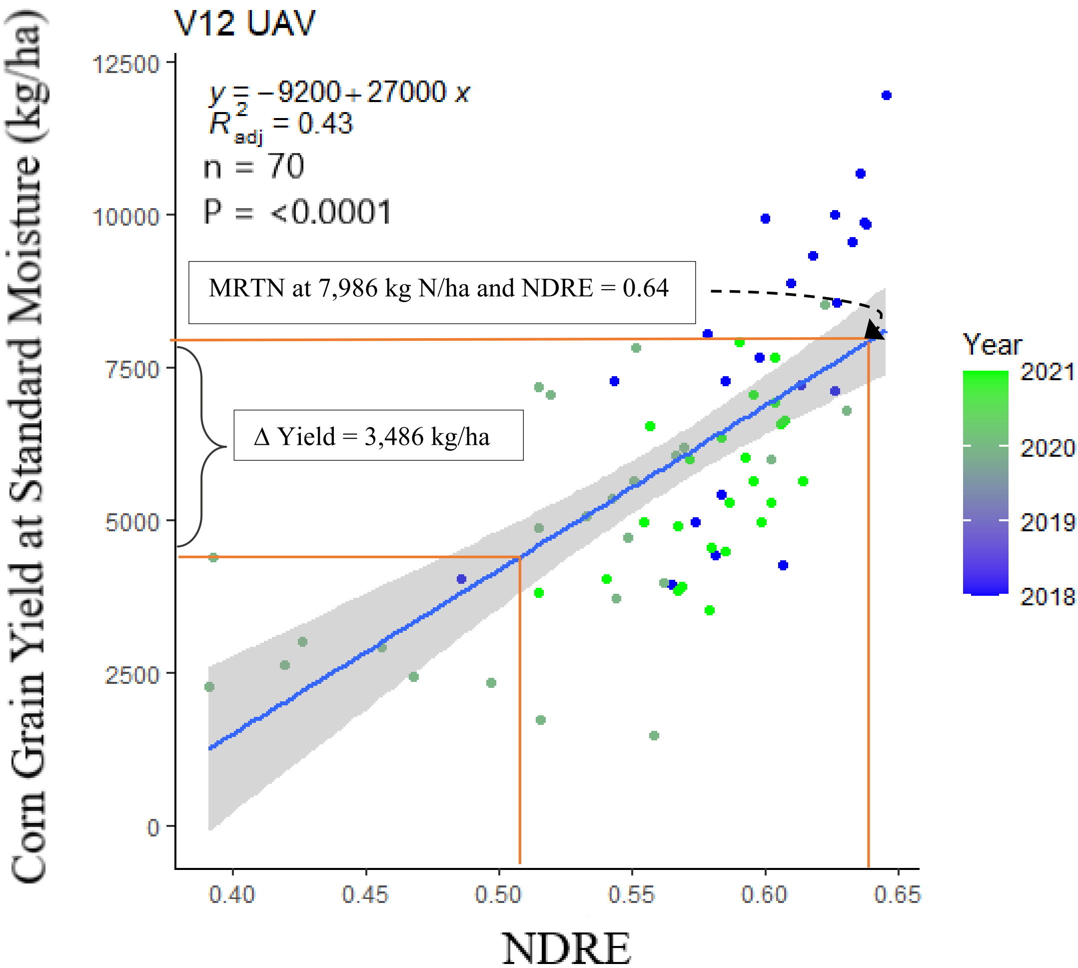

Figure A.3. Estimating N requirement from standarized canopy spectral reflectance sensed by UAV at V12 using the MRTN at 7,986 kg/ha and a sensed yield of 4,500 kg/ha.

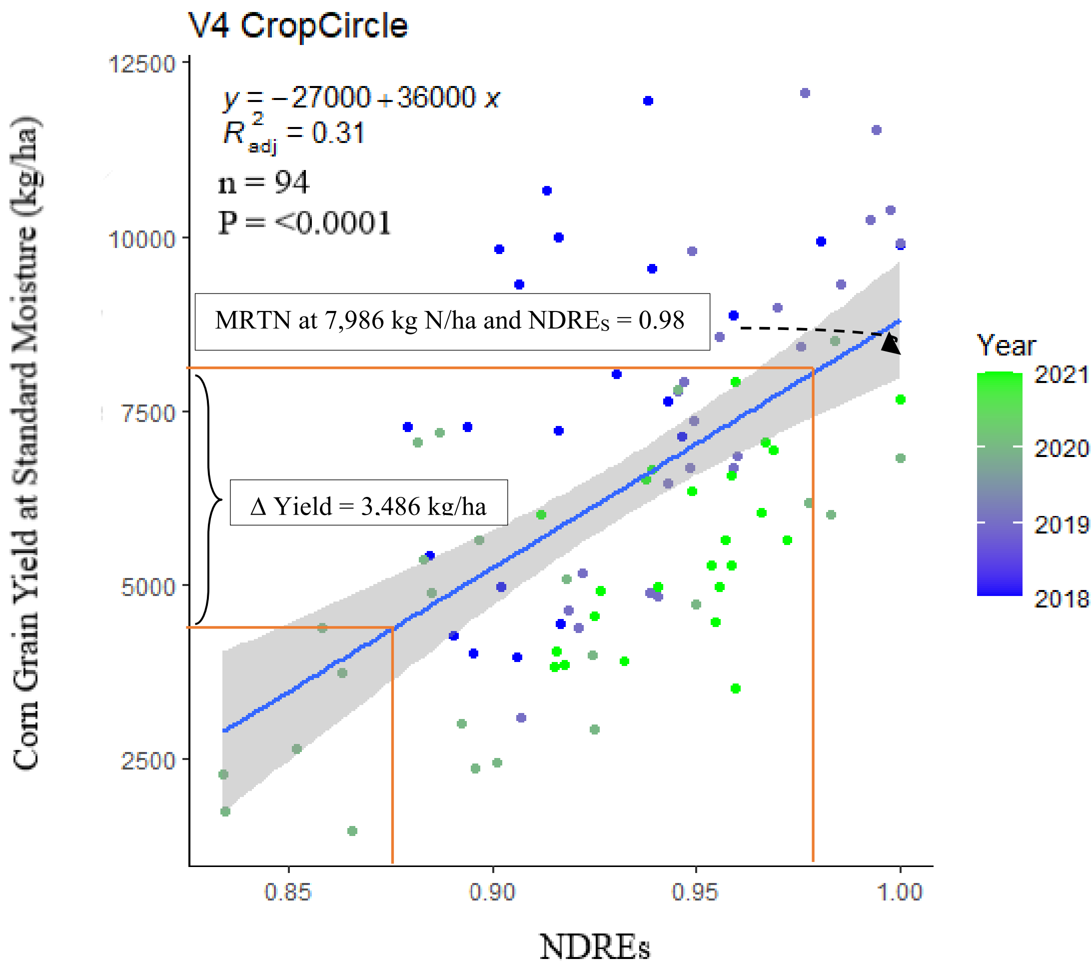

Figure A.4. Estimating N requirement from standarized canopy spectral reflectance sensed by CropCircle™ at V4 using the MRTN at 7,986 kg/ha and a sensed yield of 4,500 kg/ha.

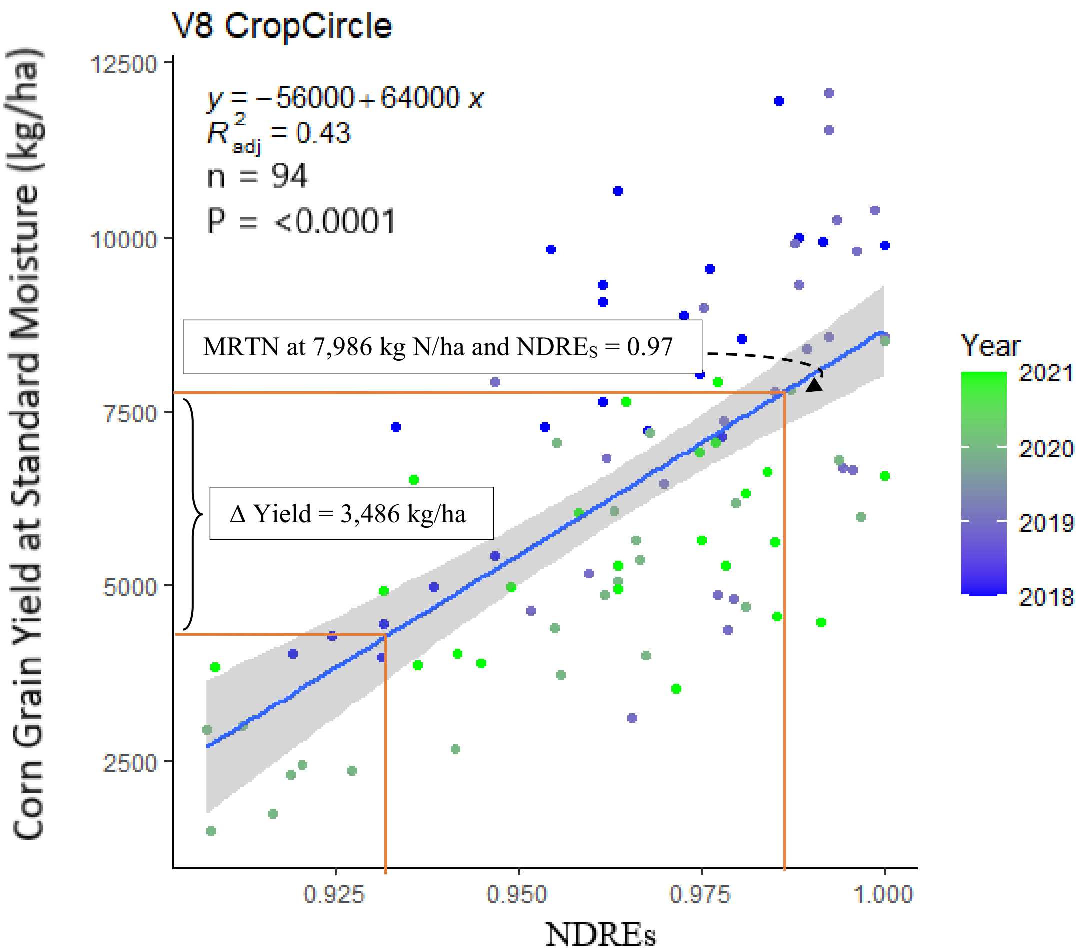

Figure A.5. Estimating N requirement from standarized canopy spectral reflectance sensed by CropCircle™ at V8 using the MRTN at 7,986 kg/ha and a sensed yield of 4,500 kg/ha.

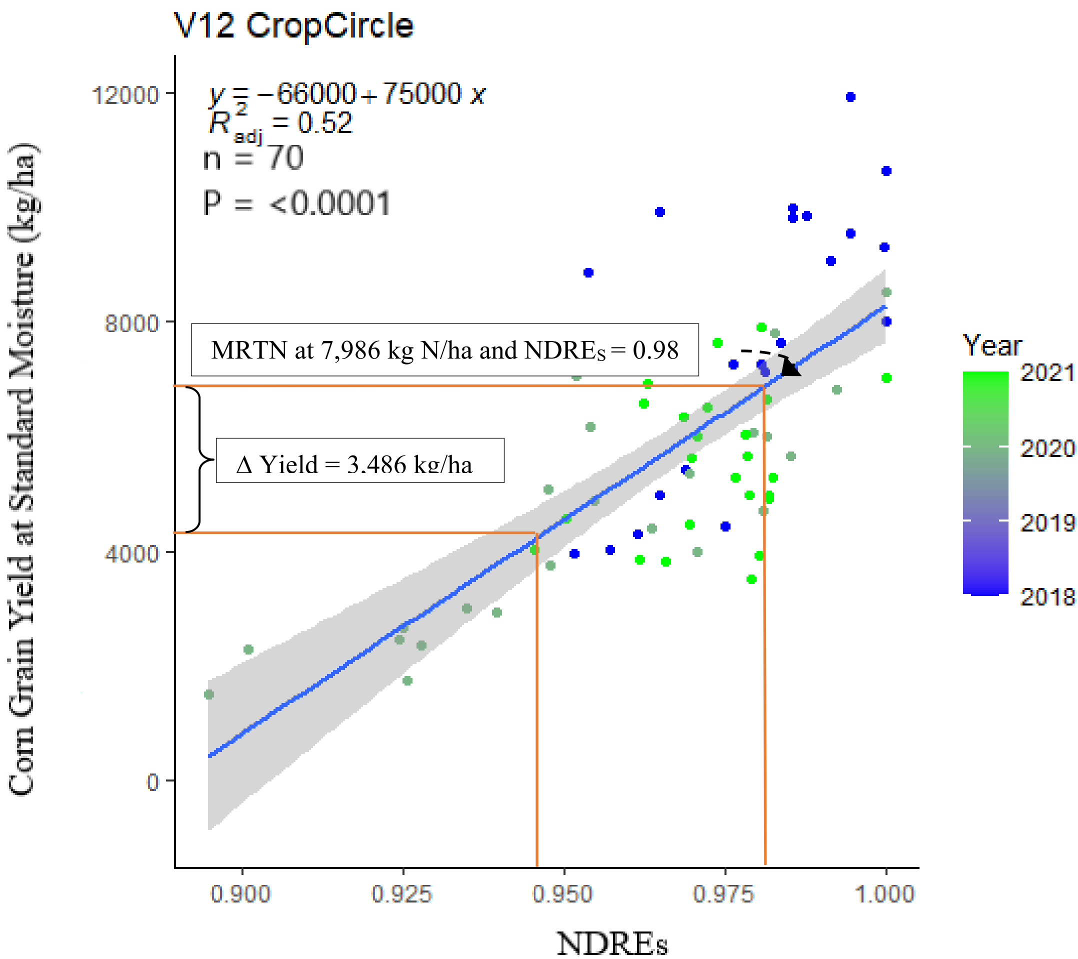

Figure A.6. Estimating N requirement from standarized canopy spectral reflectance sensed by CropCircle™ at V12 using the MRTN at 7,986 kg/ha and a sensed yield of 4,500 kg/ha.

Appendix B- Scatter plots illustrating the realtionship between corn grain yield, NDRE and NDREs during the four years at differernt corn developmental stages

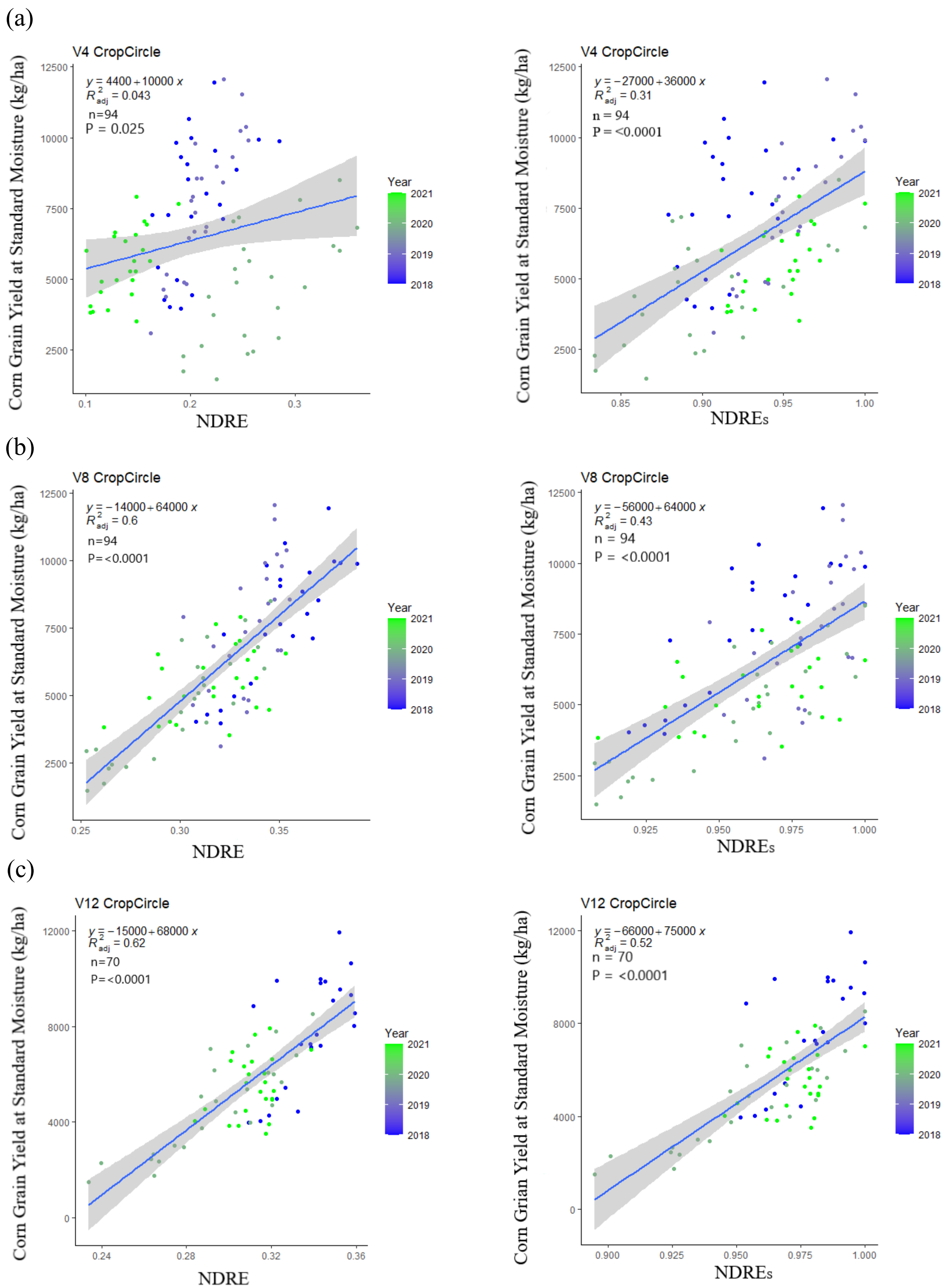

Figure B.1. Predicted corn grain yield in relation to NDRE and $NDRE_S$ values at corn developmental stages V4 (a), V8 (b) and V12 (c) using the CropCircle^{TM}.

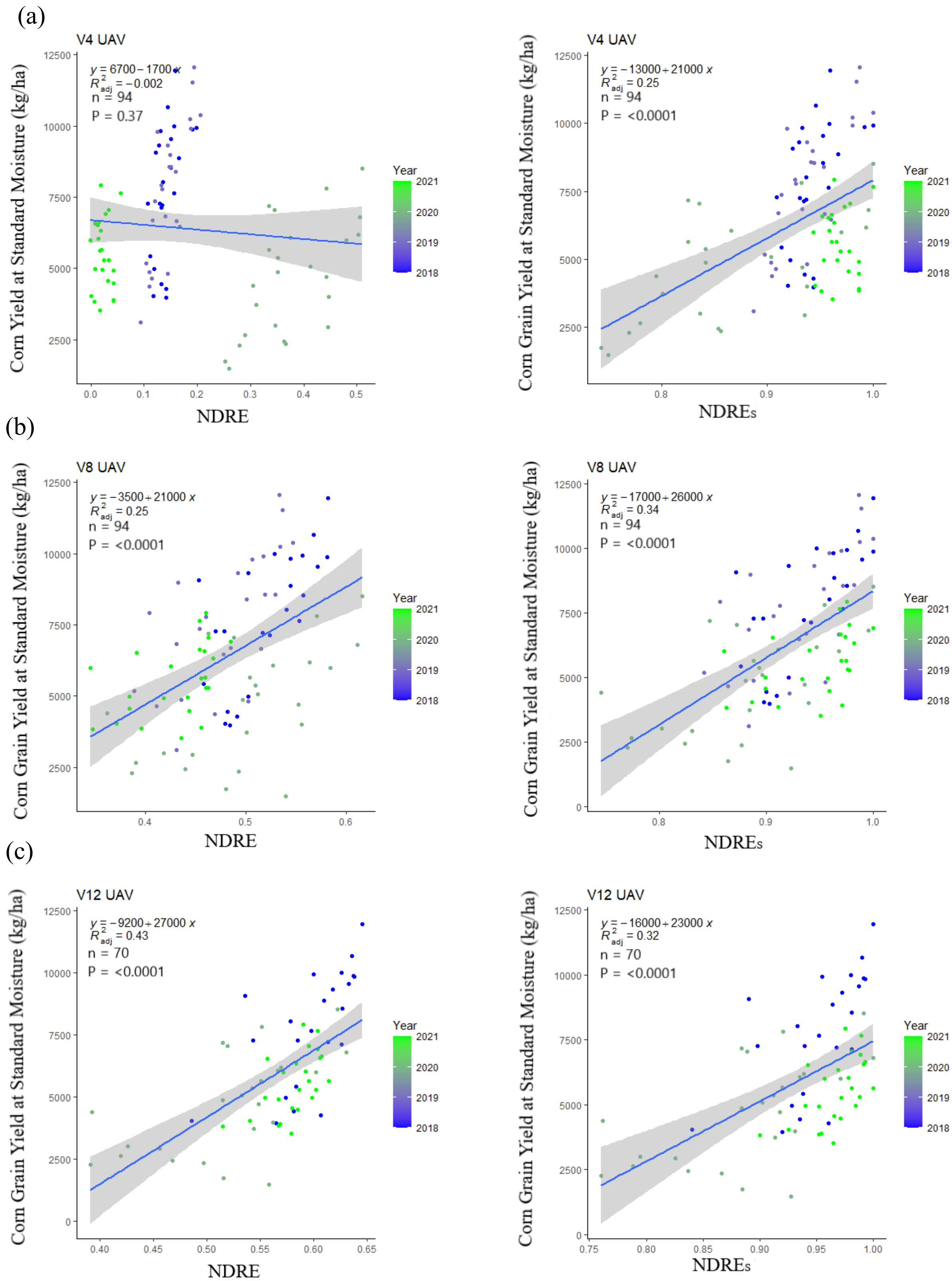

Figure B.2. Predicted corn grain yield in relation to NDRE and NDREs values at corn developmental stages V4 (a), V8 (b) and V12 (c) using the UAV.

Appendix C- Scatter plots illustrating the realtionship between corn grain yield, NDVI and NDVIs during the four years at differernt corn developmental stages

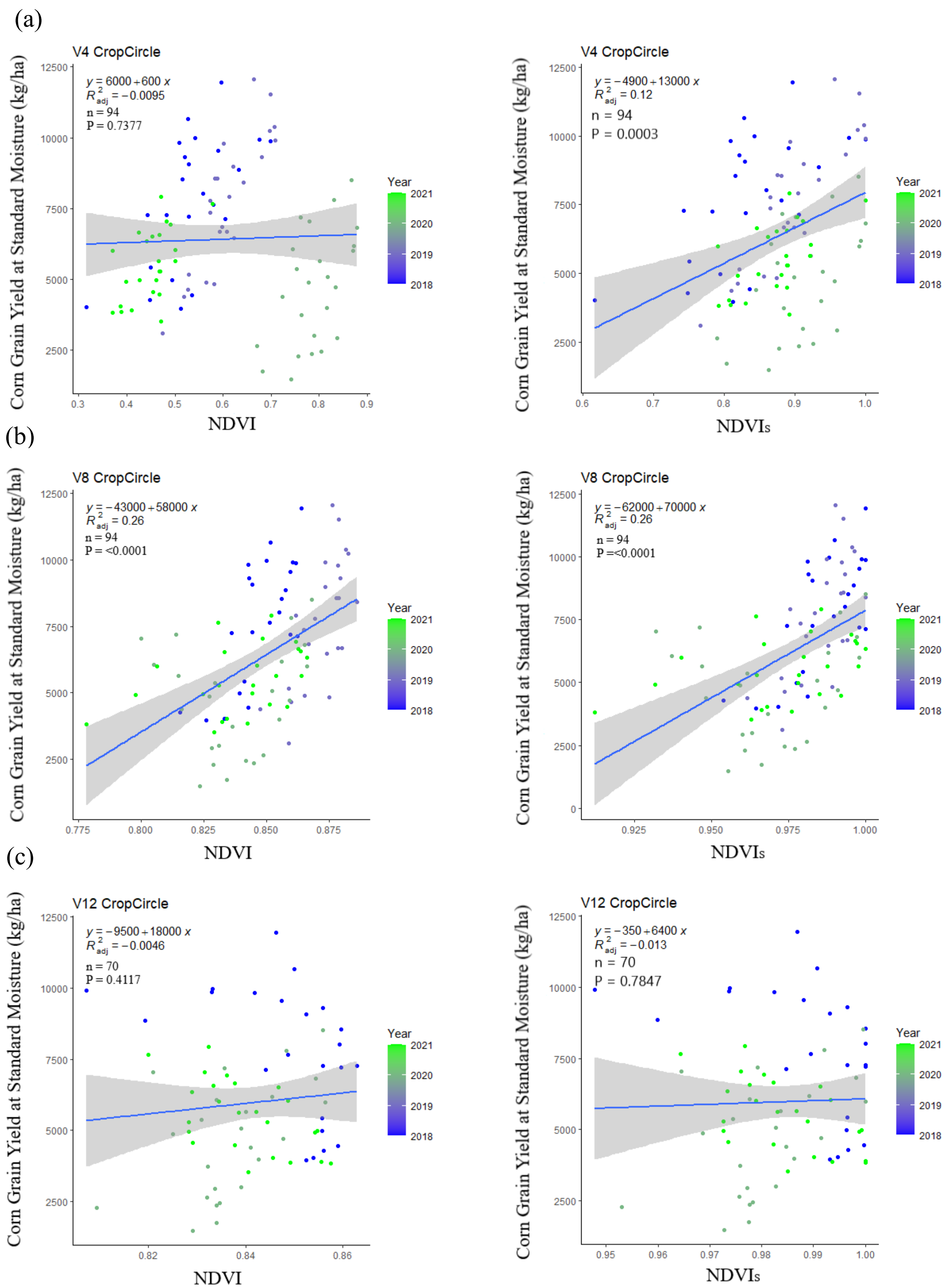

Figure C.1. Predicted corn grain yield in relation to NDVI and NDVIs values at corn developmental stages V4 (a), V8 (b) and V12 (c) using the CropCircle™.

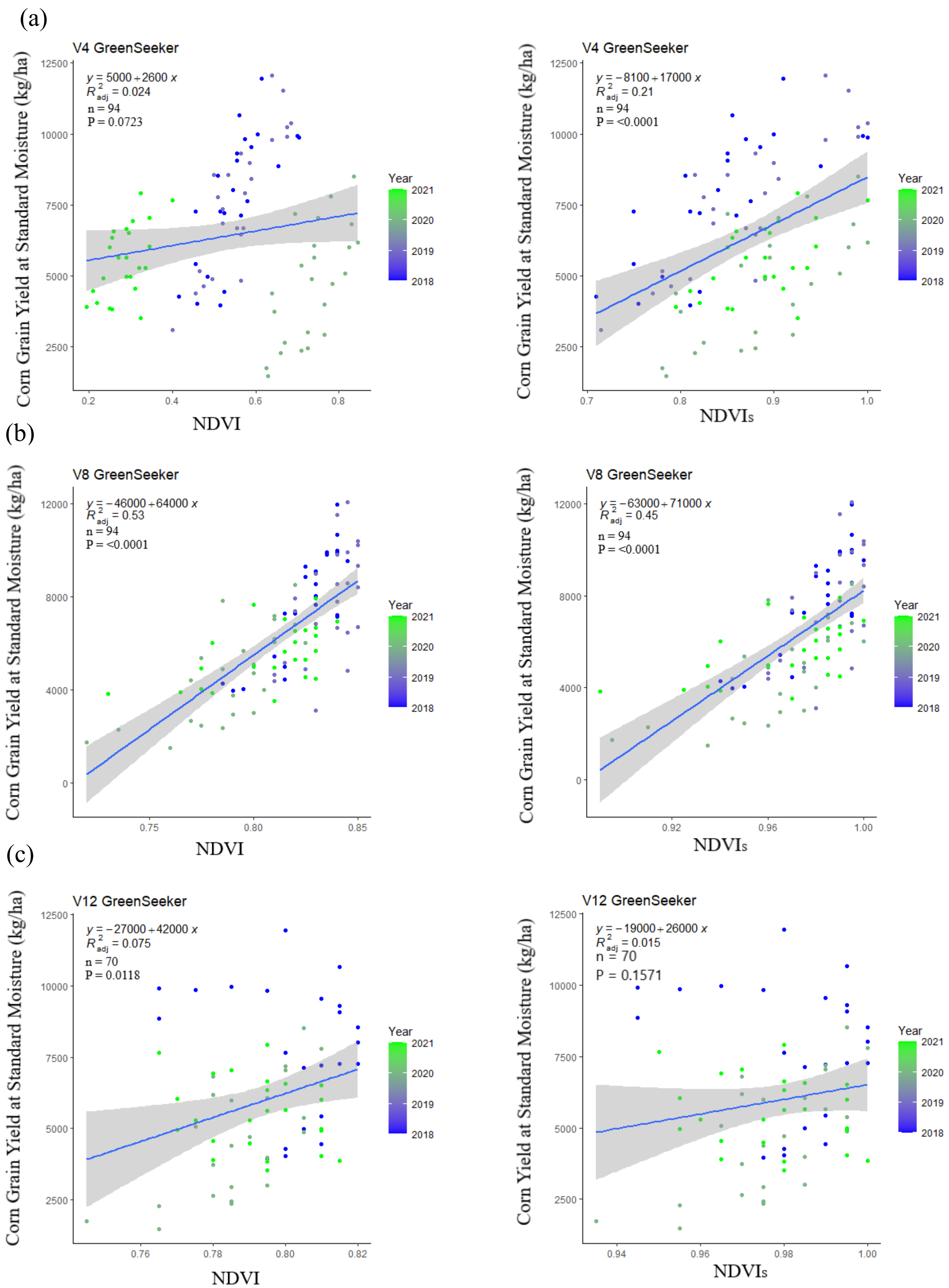

Figure C.2. Predicted corn grain yield in relation to NDVI and NDVIs values at corn developmental stages V4 (a), V8 (b) and V12 (c) using the GreenSeeker® .

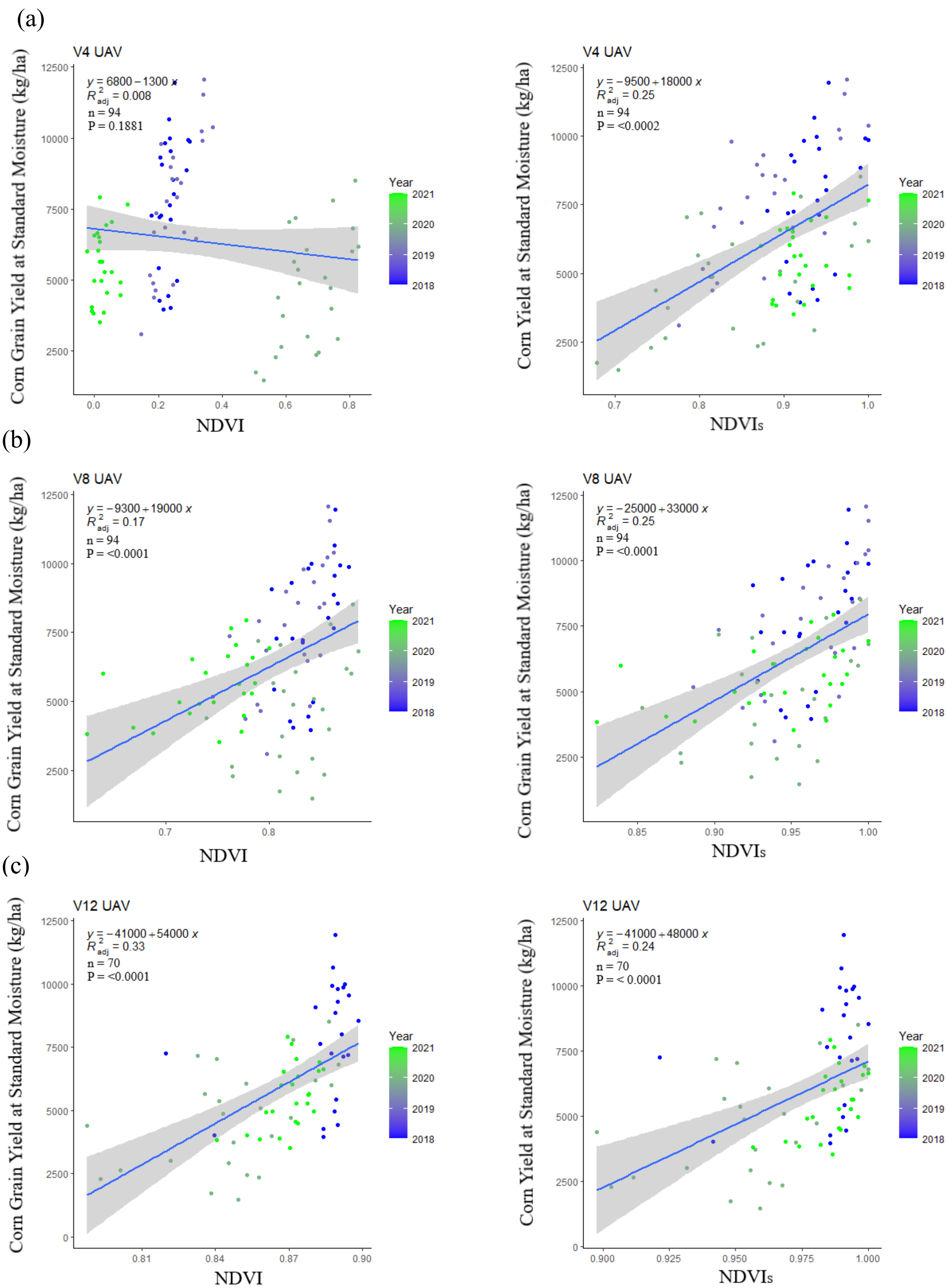

Figure C.3. Predicted corn grain yield in relation to NDVI and $NDVI_S$ values at corn developmental stages V4 (a), V8 (b) and V12 (c) using the UAV.