# USING MID-SEASON NDVI DATA FROM DRONES TO PRODUCE VARIABLE RATE FERTILIZER MAPS IN WHEAT

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**Title**

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The Supervisory Committee certifies that this ***disquisition*** complies with North Dakota State University's regulations and meets the accepted standards for the degree of

**MASTER OF SCIENCE**

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## ABSTRACT

Variable rate prescription maps can improve nitrogen use efficiency within a field by directing N applications where it is needed. If NDVI collected with a drone could be used to predict yield, it also could be used to develop N rate prescription maps. Experiments on wheat were carried out in farmer fields and in small plots. Small plot experiments consisted of six rates of nitrogen and NDVI was collected from sensors on a drone and was correlated to yield and protein after harvest. NDVI measurements were also collected from farmer fields that had a nitrogen rich strip applied to the field along with a nitrogen poor strip to induce crop growth variability and were compared to the farmer's fertilizer rate. NDVI did not always predict yield. The best time to predict yield was after anthesis. Additional research is needed to determine factors that affect the prediction of NDVI in wheat.

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N........................................................Nitrogen

VRT...................................................Variable Rate Technology

NDVI.................................................Normalized Difference Vegetation Index

GIS ....................................................Geographic Information System

SAS ...................................................Statistical Analysis System

ADMS ................................................Advanced Distribution Management System

UAV ...................................................Unmanned Aerial Vehicle

DAS....................................................Days After Seeding

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# INTRODUCTION

Modern farms and agricultural operations work far differently than those a few decades ago, primarily because of advancements in technology. Farmers no longer have to apply water, fertilizers, and pesticides uniformly across entire fields. Instead, they can use the minimum quantities required and target specific areas. Nitrogen is an essential macronutrient that impacts yield and quality in crop production, plays a critical role in the process of photosynthesis, is of vital importance to the physiology of plants, and is required in comparatively large amounts. Varying the rate of nitrogen based on zones that vary in their productivity can be an important component of a precision agricultural program. Determining production zones is a first step in variable nitrogen rate application programs. NDVI maps from drones have been used to direct in-season fertilizer applications on corn and other crops. Perhaps drone-generated NDVI maps developed from drone-mounted sensors could also be used to determine productivity zones that could be used to develop nitrogen rate prescription maps. The objectives of this research were to determine if mid-season NDVI or other sensor data collected from drone can be an effective method of developing these maps when coupled with N rich and N poor strips.

# LITERATURE REVIEW

## Wheat in the World

Some of the earliest humans discovered that wheat held a special value, as food, something mankind has been researching and working to improve ever since. Back in the Stone Age, humans discovered that they could use rocks to grind grains of wheat to make flour. Between 3,000 to 5,000 years ago, the Egyptians discovered bread (Pruitt, 2018). Over time, researchers have developed significant improvements in the production practices of wheat and the consumption habits of US and global consumers have turned wheat into the food staple that we know today (Oder, 2016).

Norman Borlaug, a University of Minnesota plant pathologist and microbiologist, sparked the "Green Revolution," (1950s – 1960s). This revolution helped improve wheat yields in much of the world. Borlaug developed successive generations of wheat varieties with broad and stable disease resistance with exceedingly high yield potential. He was awarded the 1970 Nobel Peace Prize for a lifetime of work to feed a hungry world (Oder, 2016).

Today, the United States is the world's fourth leading producer of wheat. China, the European Union and India produce more wheat than U.S farmers. Wheat research is especially important in the effort to ensure a sustainable global food supply for current and future generations because more foods are made with wheat than any other cereal grain (Oder, 2016).

## Importance of Nitrogen in Wheat

Nitrogen (N) is a building block of enzymes that are key catalysts and are essential for all known forms of life. Nitrogen acts as a key component of molecules used in photosynthesis and in enzymes that catalyze other important biochemical reactions in plants. It is also an important elemental component in chlorophyll, the biomolecule which allows plants to absorb energy from light to promote growth. In addition, N is a component of amino acids, the building blocks of proteins (Bell, 2016). Without nitrogen, plants would not be able to reproduce, create new cells, repair damaged cells, or be able to carry out important functions for survival. When nitrogen is limiting, plants are unable to carry out internal functions sufficiently or efficiently, which reduces growth, vigor and productivity and when extreme may result in the death of the plant (Tajer, 2016).

Nitrogen is the most important nutrient in terms of quantity used by crops. Furthermore, it is the most difficult to efficiently manage in the cropping system. Nitrogen fixation, assimilation, ammonification, nitrification, and denitrification are all components of what is called the Nitrogen Cycle that illustrates the complexity of the chemistry of nitrogen and how it can be lost from crop use. $N_2$ can be converted into inorganic nitrogen compounds through nitrogen fixation through the process of ammonification, the remains of living things are decomposed by microorganisms. Nitrification involves transforming soil ammonia into nitrates which plants can incorporate into their own tissues. Nitrates can also be metabolized by denitrifying bacteria, resulting in gaseous forms of nitrogen, including $NO_2$ and $N_2$ lost from the soil (Rafferty, 2014).

The form of N a farmer chooses should depend on how serious a problem he has with denitrification, leaching, or surface volatilization. Cost of N, labor, equipment and power availability are other considerations when choosing a fertilizer source (Vitosh et al., 2000). Leaching losses of N occur when soils have more incoming water (rain or irrigation) than the soil can hold. Surface volatilization of N occurs when urea forms of N break down and form ammonia gases and where there is little soil water to absorb them (Sawyer, 2007). High soil pH and high temperatures cause higher rates of volatilization because they increase soil concentrations of ammonia dissolved in soil water and warm soil water cannot hold as much ammonia gas (Jones et al., 2013).

The timing of N fertilizer applications is an important factor affecting the efficiency of fertilizer N because the interval between application and crop uptake determines the length of exposure of fertilizer N to loss processes such as leaching and denitrification. Timing N applications to reduce the chance of N losses through these processes can increase the efficiency of fertilizer N use (Vitosh et al., 2000).

The efficacy of time of application depends on soil texture, drainage characteristics of the soil, amount and frequency of rainfall or irrigation, soil temperature and, in some situations, the fertilizer N source (Sawyer, 2007). Putting nitrogen down in the fall is a common practice for farmers. The fertilizer is less expensive and there is not as much demand allowing for it to be applied within the desired timeframe. Some apply the fertilizer at planting. The current recommendation is for farmers to apply some or most of it in-season (Vitosh et al., 2000). If farmers apply N in-season, they are able to take into account more of the current season's weather when deciding on the amount to apply. If the field doesn't need it, you save money. With benefits can come challenges. There are challenges with doing in-season applications as well. If a farmer waits and the field became too wet to make an application, they may miss out completely (Jackson, 2018).

Many variables involved in soil and crop management can influence N cycling and the availability of N for plant use in the ecosystem. Decision-making regarding N application to land must consider adjustments to crop requirements based on efficiency of N uptake (particularly in the case of production agriculture) and other aspects such as soil, climate, and management practices (Tajer, 2016). The difference between the crop N requirement and the available soil N from the various sources is normally corrected by fertilization. However, a major problem exists in determining what constitutes sufficient fertilizer N. One must consider the crop, weather, soil properties, fertilization practices (time of application, rate, and placement), and the N source (Hermanson et al., 2000).

To aid farmers with N management decisions, many different N recommendation tools have been developed over the years. Traditionally, farmers have applied enough nitrogen to carry them through the growing season, based on previous experience. However, we've learned through various research that having a management plan is key to nitrogen management (Jackson, 2018). For example, in dryland systems, higher rates of available N per bushel was necessary to maximize production, compared to well-managed irrigated wheat which required a lower rate of available N for each bushel (Bell, 2016). Typically, the more productive the system, the greater the N use efficiency and the less N required per bushel to maximize yield, even though more total N would be required (Jackson, 2018). Nitrogen is one of the highest input costs for farmers, but it is incredibly difficult to know how much nitrogen to put on a field, as well as when it should be used in order to optimize yield and the net return on investment. If you put on too much, you're not going to increase the yield beyond the optimum yield point, at which point, the farmer is paying for something that isn't benefitting the operation. The same goes for applying too little nitrogen on. In that scenario, the farmer is not achieving optimum yield. It is a balancing act (Hudson, 2015). A grower could also have a large variation in the amount of N needed to optimize yield within one field. More nitrogen may be needed in one area and not as much in another; it's a complex issue (Jackson, 2018).

Applying N at the right rate is one of the most critical management practices farmers can implement to improve NUE. While it is not possible to achieve 100% NUE, applying less N fertilizer improves NUE. Applying too little N fertilizer, however, will limit yields, while excessive N rates result in low NUEs. One method to optimize the N fertilizer applications is to apply N close to the economical optimal N rate (EONR), or the rate at which any additional N starts to decrease profitability (Lu and Petkova, 2014). However, this is challenging due to the uncertainty of the EONR value for any given environment. This uncertainty arises due to the number of abiotic and biotic factors. One of these factors is the uncertainty of around how much N will be supplied by mineralization in a given season. Nitrogen mineralization is the process by which microorganisms' breakdown organic-N to inorganic-N. Soils with sufficient mineralization can provide adequate N, so there is little or no response to N fertilizer applications (Cassman et al., 2002).

When soil available N is low, yield and protein content can be impacted. As more N becomes available, yield typically increases first in wheat. When the maximum yield is reached, protein will then increase with little increase in yield. As N is applied beyond these levels the wheat plant will use the excess required to support the environmentally-dictated yield to increase grain protein concentration. If high yields and protein are desired by the farmer, high levels of N fertilizer must be applied. Proper timing of nitrogen fertilizer applications to high yielding varieties might be another means in attempting to achieve high yield and high protein, particularly in wetter years on soils susceptible to leaching or denitrification (Brown et al., 2005). Wheat is thought to have a protein-yield threshold, meaning that at some level of soil nitrogen, increased levels of N fertilizer will result in higher protein but will not increase yield (Abedi et al., 2011). Research in Saskatchewan suggested that it is possible to increase the grain protein content up to a maximum of 160 g $kg^{-1}$%, while maintaining or increasing the yield, but beyond 160 g $kg^{-1}$%, protein, yield increases would cease (Jones and Olson, 2012).

A general procedure in developing a set of fertilizer N recommendations is to evaluate the relationship between yield and N application rate in situations where no other nutrients or pest problems limit yield. Soil testing is used to determine the adequacy of plant nutrients and to determine background levels of N. Once the relationship has been determined for a variety of situations over a number of years, yield response curves can be developed. From these curves, the researcher can determine the crops EONR. In the past, recommendations were made for yield goals at or near maximum yield. More recently, the idea of targeting the economic optimum yield (which is generally less than the maximum yield) has become more popular. Using the economic maximum yield approach requires including fertilizer costs when making fertilizer recommendations by converting the yield response curve to a set of recommendations (Hermanson et al., 2000).

Growing wheat with high grain protein begins with selecting an appropriate variety followed by management practices that increase N availability late in the season. Using cultural practices or adding other nutrients to increase yield without adding additional N can reduce rather than increase protein. Drought-stressed wheat may have higher protein content because of lower yield. Even in irrigated systems, withholding water late-season generally increases protein (Abedi et al., 2011). However, there are times when withholding late-season moisture can reduce N availability and uptake, which can reduce protein.  With high yields, more in-season N per acre is required to increase protein than with low yields; that is, the protein increase from a given amount of N is less for high yielding scenarios than for low yielding ones (Jones and Olson, 2012).

## Precision Agriculture

Precision agriculture (PA) is considered a new approach to farming that requires new technologies and skills. Precision agriculture is conceptualized by a system approach to re-organize the total system of agriculture towards a low-input, high-efficiency, sustainable agriculture. The impact of precision agriculture technologies on agricultural production is expected in two areas: profitability for the producers and ecological and environmental benefits to the public. Agricultural industry is now capable of gathering more comprehensive data on production variability in both space and time. The desire to respond to such variability on a fine scale has become the goal of precision agriculture (Canis, 2015). Whether farm managers decide to adopt new technologies or not is complex, but most account for the full costs and benefits of the proposed investment (Tey et al., 2012). A significant investment of capital and time are needed to incorporate PA into a farming operation but adopting the new technologies may offer cost savings and higher yield through more precise management of inputs (Schimmelpfennig et al., 2011). These benefits derive from the efficient use of yield-monitoring harvesters and yield mapping with Global Positioning Systems (GPS), tractor guidance systems, soil mapping, and variable-rate input application. These are the most popular PA technologies and although they have the potential to aid farmers in reaching higher profits, the adopting rates of these technologies are low with variable-rate technology (VRT) the lowest. The profits on these technologies may be small yet positive, which may help explain the slow adoption rate. Taking farm size into consideration, large farms are more likely to adopt PA technologies. VRT adoption is lower than for the other technologies on all farm sizes (Schimmelpfennig, 2016).

Uniform application of crop production inputs does not allow optimum efficiency or profitability because factors that affect crop production are rarely uniform within fields. Properly implemented, variable rate technology (VRT) more precisely applies required inputs. It has the potential to improve, or ideally maximize efficiency of inputs and profitability of individual fields by targeting application where needed at optimum rates (Sawyer, 2018).

Using variable rate fertilizer application technologies producers apply different rates of fertilizer to define zones across fields. Customized application of fertilizer is accomplished with machinery attachments that can vary the rate of application from GPS controls in the cab of tractors. Geolocated data from yield and soil maps or from guidance systems can be used to pre-program application equipment to apply desired levels of inputs at different locations in a field. Controllers adjust the levels of inputs coming from each nozzle on command from a computer program that uses the geo-referenced data points (Schimmelpfennig, 2016).

No definitive answer exists as to whether VRT should be used in every field or if it is the best crop input management for all farmers. Whether to use VRT or not depends on the expected crop response to nutrients, value of the crop, characteristics of variability, capability to manage the new technology, importance of benefits, environmental improvement and many more factors (Sawyer, 2018).

The capital cost of farm implements equipped with VRT capabilities is considerable, especially when specialized machinery with integrated sprayer or seeding equipment must be scrapped (Liu et al., 2006). For this reason, many producers, particularly on smaller operations, have opted to hire service providers when choosing VRT. Only 21 percent of the PA studies reviewed by Griffin et al. (2004) included human capital costs, but operator time and effort were found to be a substantial cost for VRT and a likely reason for outsourcing the service (Schimmelpfennig, 2016).

Research shows VRT can improve input efficiency and field profitability, but it indicates that positive economic return to VRT application does not always occur (Liu et al., 2006). Several possible shortcomings affect potential benefits, which include (i) the crop is not responsive to the input (ii) the crop-input response function used is not specific or appropriate (iii) within-field variation is in a range that does not affect yield (iv) variation is small or does not exist, and therefore VRT cannot improve upon results from a uniform rate (v) variation is not correctly (or at least adequately) identified, measured, or delineated (mapped) (vi) measurement and recommendation practices available today are neither adequately accurate or reliable for VRT (vii) identified variation is not correctly managed or there is incorrect interpretation of expected crop response and (viii) costs of implementing VRT (sampling, mapping, equipment, and personnel) outweigh the value of crop yield increase or input saving (Sawyer, 2018).

At today's crop value and cost of technology, VRT may not always be economical. It must improve profitability of fields and provide environmental benefits, or it should not be used by farmers. Many technological innovations have been presented but development of agronomic and ecological principles for optimized recommendations for inputs at the localized level is generally lagging. Many farmers are uncertain as to whether to adopt available precision agriculture technologies on their farms. Variable rate technology is one of many management tools with the potential to optimize crop yield and profitability. If no other benefit occurs, at least the VRT process demands critical field evaluation and management (Sawyer, 2018).

An unmanned aircraft vehicle comprises an aircraft with no onboard pilot, controlled from a remote operating station. The aircraft is sometimes referred to as an unmanned aerial vehicle (UAV) or a drone (Canis, 2015). Currently, the way to get aerial images of a field are either satellite images or possibly airplanes. These are limited by the resolution of their images and how often they fly over a field. The 15-cm resolution of UAV cameras is over 40,000 times better than the most commonly available satellite data and even 44 times better than the best commercial satellite images. Planes and satellites also fly above the cloud level and images can be obstructed in bad weather. Drones have the advantage of being able to monitor a field every week throughout the growing season. Satellites have a week or two delay before the images are available. Drone operators runs on their own schedule and do not need to rely on the satellite flight path. This also means they have the flexibility to re-fly over trouble spots or move in for a closer look (Zhang et al., 2002).

Crop scouting is often done by interns on foot. At the ground level, it is hard to cover the entire field, especially late in the season for a crop like corn when the plants are taller than a person's head. Farms continue to increase in size, so more acres per enterprise must be scouted. Once an entire field is covered by a drone, trouble spots can be identified and targeted for scouting on foot (Stehr, 2015). Insurance companies can use drones to get a better idea on the extent of damage after a hail storm, easily determining whether a field has 70% compared with 90% loss.

Yield monitors were first used on combines in the 1990s and have not changed much since, but their popularity has. New grain combines are marketed with GPS-linked yield monitors as standard equipment (Schimmelpfennig, 2016). More than 70 percent of U.S. farmers have GPS-linked yield monitors on their harvest equipment (Franzen, 2018). Famers use GPS-based computer mapping of yield to help customize crop management in fields. When areas in the field are lower yielding, the farmer either adds inputs to raise yields or reduces inputs on areas that are lower yielding and are less likely to be profitable (Schimmelpfennig, 2016). Yield monitor maps can be a powerful tool to explain the yield drag in salty areas of the field and the need to management these areas differently. Yield maps also are a valuable archive of field performance and the changes that management might have had on the fields. The archived maps can be shared with bankers or passed down to the next generation so that the things farmers learn about in their fields will not be lost to heirs. Yield maps are also useful in product testing or any on-farm research worthwhile. When strips of treatments, such as N, are applied across a field, the stream of yield data from the strips can be analyzed statistically. Yield data from multiple years results in a good tool on which to base nutrient management zones for variable-rate nutrient application (Franzen, 2018).

Although a variety of information can be helpful, yield maps will provide the backbone of most successful for VRT prescriptions. Yield maps over time are an excellent starting place for developing management zones. Soil series information is readily available but should not be used alone to create management zones. Remote sensing imagery, software systems (SMS), soil tests, or soil type maps could be useful in creating fertilizer maps (Schimmelpfennig, 2016).

A more advanced camera filter for crop scouting is one that takes near-infrared images. Healthy plants reflect both green and infrared wavelengths of light. When they are stressed from pest, nutrient, or drought, the type of light reflected changes and can be picked up by the cameras. On the pictures, healthy plants will appear bright red, while stressed plants or weeds will look darker red. These bands of light can be used to calculate a normalized difference vegetative index (NDVI). The formula for NDVI is the ratio of near-infrared light (NIR) minus visible light (VIS) over near-infrared light plus visible light, as shown NDVI = (NIR – VIS)/ (NIR + VIS) (Taipale, 2018). Overall, NDVI is a standardized way to measure healthy vegetation (Grassi, 2016).

Though many will argue that ground-based inspections combined with satellite imagery along with a dedicated grid soil sampling program is more practical for refining nitrogen, phosphorus and potassium applications in agriculture, drones do have a fit. A drone service start-up company in the United States has used NDVI maps to direct in-season fertilizer applications on corn and other crops (Grassi, 2016). By using drone-generated variable-rate application (VRA) maps to determine the strength of nutrient uptake within a single field, the farmer can apply 300 kg/ha of fertilizer to struggling areas, 200 kg/ha to medium quality areas, and 150 kg/ha to healthy areas, decreasing fertilizer costs and increasing yield (Veroustraete, 2015).

Tailoring nitrogen application rates to more exactly meet crop needs should increase profitability, reduce environmental risk, and may result in higher and more consistent grain quality. The key to success and eventual adoption of variable-rate nitrogen management will be the development of decision-making criteria that can accurately predict nitrogen rates that are economically optimum and environmentally sustainable (Grisso et al., 2011).

For nitrogen applications, the concept is that the amount of fertilizer needed at a particular location within the field can be determined by implementing a nitrogen-rich strip at planting or shortly thereafter and comparing spatial variability of crop growth across the field to crop growth from the nitrogen strip (Lowenberg et al., 2019). The nitrogen-rich strip provides an area in which nitrogen is not the yield-limiting factor nitrogen application at planting. NDVI readings are collected from the nitrogen-rich strip. Subsequently, as the fertilizer applicator covers the field, the sensors read NDVI values, compare them to the NDVI values from the nitrogen-rich strip, and apply an adjusted amount of nitrogen. Instead of the nitrogen-rich strip consisting of one rate across the field, a range of nitrogen rates is applied across the field. This provides a benefit in that growers can see actual response to a range of nitrogen rates and when they are setting ranges for variable-rate application, they have more information about how to appropriately establish the breaks for the assorted nitrogen rates (Grisso et al., 2011).

Mixed results indicated that although there may have been some positive net returns, Lambert and Lowenberg-DeBoer did not have enough confidence to support the general assertion that similar results could be achieved under similar circumstances. Oftentimes, conclusions in these reports indicated that more research needed to be done in order to reach a valid conclusion (Lowenberg et al., 2019).

Currently, most of the VRA technologies are commercially available, but they need an investment of time and thought of how to implement the prescription maps. The decision to use VRA and the prescriptions for varying inputs are truly site-specific. Not every farm or field will show an economic benefit from VRA, but these technologies offer opportunities for growers to increase both the production and environmental efficiencies of crop production and should be carefully evaluated (Grisso et al., 2011).

There have been numerous studies documenting the correlation between NDVI and crop yield at the national, regional, and county level (Maselli & Rembold, 2002). Tucker (1979) determined that the time integrated NDVI is largely correlated with crop yields when the vegetation is at the maximum level of greenness. Some studies focus on intra-annual variability, how the correlation between the vegetation index and crop yields varies by the planting date (Basnyat et al., 2004). D.M. Johnson (2014) found that the week where the association of yield and NDVI is at its peak in the beginning of August. A study conducted by Chang Xu at Ohio state university found that the response of yield to NDVI is different across locations, showing spatial heterogeneity of responses. For some counties in the Northern states, yield is highly related with July NDVI, whereas for other counties located in the south, August NDVI is a better indicator of yield.

A study in Japan showed strong correlations between NDVI and yield that were observed at the early reproductive stage or the late ripening stage for the direct-seeded rice, and at the middle reproductive stage of the early ripening stage for the wheat. The result that the NDVI values were highly responsive to fertilizer application levels indicated the potential for early detection of nitrogen deficiency (Guan et al., 2019).

Similarly, a study in Australia suggest the possibility of using NDVI measurements at maturity as a potential tool to identify areas with higher or lower defoliant application needs to make prescriptive applications in order to increase harvest efficiency. Nevertheless, further definition of relationships for this purpose are required (Ballester et al., 2017).

In the subsequent studies on UAV-based yield estimates, rape and barley crops were investigated. High correlations between NDVI and GNDVI values and the respective yield reference data were found. These results were obtained despite a very late flight which had been carried out shortly before harvest (Nebiker et al., 2016).

## OBJECTIVE

The objective of this research is to determine if NDVI data collected with UAVs and/or other sources can be used to define zones within a field that require specific management practices in order to optimize yield and nitrogen fertilizer inputs. Ultimately, the data collected in this project will be used to generate prescription maps that will guide the application rates of nitrogen within a field.

## MATERIALS AND METHODS

Experiments were carried out in small plots in 2018 and 2019 and in farmer fields in 2019.

### Small Plot Experiments

The small plot experiments were established at North Dakota State University's Seed Farm, near Casselton, ND and on a farmer's field near Ada, MN, in 2018 and in Steele County, near the town of Mayville and in Grand Forks county near Thompson, ND, in 2019. These experiments were designed as randomized complete blocks (RCBD) with four replications. Treatments consisted of six rates of N (0, 44, 89, 134, 179 and 224) kg $ha^{-1}$. Urea, the fertilizer used to supply N was applied by hand which was then incorporated to about 10 cm using a light cultivator. In 2018, the soil test showed Casselton, ND had 44 kg $ha^{-1}$ N, 22 kg $ha^{-1}$ P, and 5% organic matter in the soil. In Ada, MN the soil test showed 30 kg $ha^{-1}$ N, 10 kg $ha^{-1}$ P, and 3% organic matter. In 2019, the soil test showed Steele Co. had 52 kg $ha^{-1}$ N, 20 kg $ha^{-1}$ P, and 5% organic matter. Grand Forks had 31 kg $ha^{-1}$ N, 6 kg $ha^{-1}$ P, and 5% organic matter. The wheat was then seeded in plots that consisted of 7 row spaced 18 cm apart and 3.7 m long. Planting dates were May 30th in 2018 and May 17th, in 2019. The seeding rate was 3.46 million seeds $ha^{-1}$ and the variety used in all experiments was Faller. Weeds were controlled with a mixture of fenoxaprop, pyrasulfotole, bromoxynil octanoate, and bromoxynil heptanoate (Wolverine Advanced™ at 1.9 L $ha^{-1}$) applied at the 4-leaf stage of wheat development.

After emergence and before the 3-leaf stage stand counts were made to ensure that plant stand was representative of farmers' fields. Plant height was also taken from soil to tip of plant just prior to harvest. Reflectance data were collected with a Micasense camera sensor mounted on a drone. The sensor collected RGB and NIR color images which were used to calculate normalized difference vegetation index (NDVI). NDVI has been found to be useful for a variety of agricultural purposes. Low NDVI values can clearly distinguish areas of the field where a crop is growing poorly when compared to those where it is not, enabling zones to be created to target the right amount of fertilizer to be applied to each spot on the field (Guan,2019). The drone used was manufactured by AGBOT, an Aerial Technology International company in Oregon City, OR. The drone was flown at 60 m with flights having a 75% overlap. NDVI data were collected at multiple stages throughout the growing season starting at the 6-leaf stage and ending at heading. The data was stitched using Pix4D, a unique photogrammetry software for drone mapping based in Denver, Colorado and processed in ArcMap using python code written by Joao Paulo Flores, a Precision Agricultural specialist at the Carrington Research Extension Center in North Dakota.

Plots were harvested with a Wintersteiger Classic plot combine and yield was measured with a combine-mounted weighing system. A sub sample of the harvested grain was used to determine test weight and moisture which were measured with a GAC 2100 moisture analyzer (Dickey John) from Auburn, Illinois. Grain protein concentration was measured on a subsample by NIR using a Diode Array 7200, an analyzer instrument manufactured by Perten Instruments NA, Inc in Springfield IL and was converted to protein percent on a 12% moisture basis.

Data were analyzed using ANOVA with Proc GLM in SAS™. Means were separated using LSD at the 5% level of probability. Regression analysis was used to explore the relationships between NDVI and yield and NDVI and protein to determine if NDVI could be useful in predicting either of these two values.

## Grower Managed Experiments

Wheat fields near Campbell, MN, Breckenridge, MN, Walcott, ND Colfax, ND, and East Grand Forks MN, were selected for inclusion in the research in 2019. In order to identify fields that were relatively uniform and representative of the area, NDVI and geographical feature of potential fields were examined from satellite imagery that was available from previous years. These data were accessed using GK Technology software, based in Halstad, MN and databases and were selected after entering the section and township data from 2015, 2016, 2017, and 2018. These values were taken into account from previous years when selecting the field and areas within a field that would be included in the experiment. We wanted to include fields that induced variability for the trials. Finally, a visit was made with each farmer at each site to communicate how the experiment was to be set up prior to the growing season.

In each experimental field, a nitrogen rich strip was applied to the field, along with a nitrogen poor strip. These strips were applied by the farmers preferred method and approximately two-three times the width of the combine header. Both of the strips were compared to the farmer's regular rate of fertilizer rate. Depending on the farmer's normal rate of fertilizer, the rich strip was 1.2-1.5 times the original rate and the poor strip was 0.75 times the normal rate. The seeding rate, variety, weed control methods and other management practices were based upon the grower's personal preference. An "as applied" fertilizer map was collected from the growers who had access to one in order to geo-reference these strips. This allowed for the exact coordinates in the field where each strip was applied to be identified. For fields without "as applied" maps, the strips were flagged out and GPS coordinates were taken for the corners of the strips using a Garmin GPS tracker. The drone and sensors described above were used to collect the spectral data used in this research. The wheat fields were flown at various stages throughout the growing season, including: three-six leaf, flag leaf, boot and heading. A specific time in the growing season was not set as we were unsure as to which stage would provide the optimal data to predict yield at the end of the season. The intent was to fly early enough in the season so an in-season application of nitrogen might be possible. Flying early enough to make an application, yet late enough so nitrogen deficiencies are visible was considered to be the ideal timing. Therefore, more than one flight was planned. Weather was also taken into consideration. Clear skies are optimal for minimal shadowing in the imagery. The drone was flown at 121m (75% overlap) to optimize the area of ground covered for the best picture possible and is the maximum altitude a drone can be flown. Mission Planner, a ground control station for the UAV, compatible with Windows, developed by Michael Oborne, was the program used to fly the drone.

In addition to flying the drone throughout the growing season, prior to harvest, samples from the various strips within the wheat fields were collected for protein analysis. Three wheat samples were taken from rich, poor and normal nitrogen strips in the field for a total of nine samples per field. Heads were cut from the wheat plant using a sharp knife. A sufficient number of heads (50-100) were taken to result in an accurate protein reading. The samples were threshed and run through the Diode Array 7200 NIR analyzer to measure protein.

After collecting imagery with the drone, the images were stitched together using a computer program called Pix4D. The drone takes a picture every second and stitching all the images together creates one solid mosaic. The drone data imagery was analyzed using Geographic Information Systems (GIS) software. Through GIS, I was able to upload the stitched map, and visually compare the differences in NDVI throughout different stages of the growing season (6-leaf, flag leaf, boot, and heading stage).

A yield map was collected from each grower at harvest from the yield monitor on their combine. Using GK technology, a yield map layer was compared to the stitched NDVI layer created from the data collected by the drone. For further analysis, the mapped data were broken up into 140 cells with equal number of cells from each of the nitrogen strips created in the farmers' fields. Each cell holds an average yield and NDVI value for that particular location of the field. NDVI and yield were then compared using regression and correlation analysis. The imagery was also provided to a local company, GK Technology, to make the prescription maps that can be used by the farmer when deciding where to apply additional (or less) nitrogen. ADMS is the software used to design several different imagery file types like JPG, TIF, BMP, SID, for instance, and data formats including ECW, DAT, LAZ and many others. ADMS can crop these large image and data types by simply using a shape file such as a field or county boundary, drastically reducing file sizes for easy filing and exporting. The zone creation methods in ADMS take image and yield data to the next level for a grower's soil sampling and zone management needs. The data put into the zone creation method in ADMS creates management zones that more accurately represent the field. ADMS creates several mathematical options for helping you to create these zones and customize them based on your knowledge of the field. Variable rate mapping starts with a process of taking one or a combination of input maps for a field. Input maps can come from many different sources such as satellite images, UAV stitched data, and yield maps. Input data can be merged together based off of GK algorithms creating management zones.

Data were analyzed to determine if the various nitrogen strips varied for yield and NDVI. In most cases, these strips were not replicated, so farms served as replicates. Additionally, ADMS software generates correlations between the various layers on the map created for the selected fields. These correlations were used for further analyses and to attempt to determine the predictive value of NDVI from a single season on yield.

## RESULTS AND DISCUSSION

### Challenges of Collecting Data with Drone-Mounted Sensors

The primary objective of this research project was to determine if NDVI data collected by a drone-mounted sensor could be used to help create prescription maps for variable rate applications of nitrogen. This type of data might be an efficient way for farmers that do not have yield maps to develop production zones within a field. Yield maps created from combine mounted yield monitors have been a traditional source of information used in creating these maps. For farmers that do not have historical maps, NDVI maps might serve as a quick and inexpensive way to guide the development of prescription maps, if NDVI can effectively predict yield. Drones are now relatively inexpensive to purchase and easy to operate. Nevertheless, I found that collecting the desired data with the drone presented many challenges in this project. Optimal weather conditions for collecting date are completely clear skies, to prevent shadowing from clouds in the imagery, and no wind, allowing the drone to fly more uniformly. Given the weather conditions we had this past summer (wind, clouds, and rain) there were very few opportunities to fly the drone. Nevertheless, each field was flown three times (flag leaf, boot, and heading) under the best weather conditions possible.

Even though currently available software makes operating a drone relatively easy, operational errors still presented significant challenges throughout this project. Unfortunately, drones do not always fly perfectly. There were multiple times that I would create the drone's route in the computer, sync the drone to the computer, and send it off, later to find that the internal compass in the drone was incorrect, therefore, the drone flew a completely different route than that programmed. Occasionally this would result in the drone crashing. Searching for a downed drone required many hours looking for it. Battery life also presented challenges. Not every field was small enough so that one battery pack was enough to power the flight duration needed to cover the entire field. This had to be planned for otherwise the drone could have run out of power and fall from however high it had been programmed to fly. Additionally, battery packs had to be checked regularly as damaged batteries may explode in the air, catching on fire, and causing the drone to crash. An important lesson learned is that collecting good data with a drone requires patience, reliable equipment and vigilance when maintaining it and while flying. Managing and manipulating the data can also be time consuming and learning how to process it and interpret it requires a significant investment and assistance from others with relevant experience. Though a drone may be inexpensive and easy to fly, I found the challenge of collecting and analyzing useful data, at least the type that we required for this project, to be significant and probably beyond the interest, available time and skills of most farmers.

## Small Plots

Small plot research was included in this overall project in order to determine if NDVI data collected with a drone could be used to predict yield and or protein when rates of nitrogen were strictly controlled within a relatively small area of the field where field conditions were likely to be uniform. This would allow us to test the hypothesis that NDVI can be a good predictor of yield when nitrogen is the main factor controlling yield. Experiments were conducted in two locations each year. Since the response to nitrogen varied between years, the data from each year are reported separately. Experimental error within a location and year were found to be homogeneous, and so data for the locations within a year were combined. Therefore, the results for each year are reported separately, but are combined over locations. In 2018, increasing the N rate from 0 to 89 kg $ha^{-1}$ resulted in a linear increase in yield. With N additions above 89 kg $ha^{-1}$, however, there was no additional yield increase (Table 1). These data suggest that only 89 kg $ha^{-1}$ of added N was needed to optimize yield. The relationship between N rate and yield was best described by a quadratic relationship when regression analysis was employed. Protein, on the other hand, increased with each increment of added N, and did not reach a plateau. This relationship illustrates the need to consider protein as well as yield when developing N recommendations for spring wheat, as the price farmers get when they market their wheat is often determined to some extent by its protein content. There was no response of NDVI to added N. Therefore, there was no significant correlation between NDVI and yield or NDVI and protein. The data suggest that NDVI was saturated and therefore could not distinguish the plots that would ultimately have different yields and protein levels. In 2019, increasing the N rate from 0 to 44 kg $ha^{-1}$ resulted in an increase in yield. This is unlike 2018, where yield increased up to the 89 kg $ha^{-1}$ rate (Table 2). These data suggest that only 44 kg $ha^{-1}$ of added N was needed to optimize yield. Protein unlike 2018 did not increase with each increment of added N. Instead, there were little differences in protein levels regardless of the amount of N applied. In general, however, protein levels were much higher in 2019 than in 2018 even though the yield levels, at least at the lower N rates, were similar. Perhaps one of the reasons for the elevated protein level in 2019 was due to the restricted grain filling rate due to a heavy incident of Bacterial Leaf Streak. There was no response of NDVI to added N. There was no significant correlation between NDVI and yield or NDVI and protein. Planting was delayed in 2019 and Bacterial Leaf Streak was problematic. These both could be factors limiting the response of NDVI, yield and protein and resulting in limited or no correlation between these traits.

Table 1. The effect of nitrogen rates on NDVI, protein, and yield average of two locations in 2018.

| Treatment | NDVI (6-leaf) | Protein | Yield |
|---|---|---|---|
| | | | Mg/ha$^{-1}$ |
| 0 | 0.79 | 13.7 | 1.74 |
| 44 | 0.80 | 13.7 | 1.98 |
| 89 | 0.79 | 14.3 | 2.13 |
| 134 | 0.78 | 14.3 | 2.12 |
| 179 | 0.79 | 14.6 | 2.15 |
| 224 | 0.79 | 14.8 | 2.09 |
| Mean | 0.79 | 14.2 | 2.04 |
| CV | 4.62 | 3.61 | 6.36 |
| LSD05 | N/S | 0.52 | 0.13 |

Table 2. The effect of nitrogen rates on NDVI, protein, and yield average of two locations in 2019.

| Treatment | NDVI (6-leaf) | NDVI (heading) | Protein | Yield |
|---|---|---|---|---|
| | | | | Mg/ha$^{-1}$ |
| 0 | 0.92 | 0.92 | 15.4 | 1.75 |
| 44 | 0.91 | 0.90 | 14.9 | 1.92 |
| 89 | 0.92 | 0.91 | 14.8 | 1.91 |
| 134 | 0.91 | 0.92 | 15.0 | 1.86 |
| 179 | 0.91 | 0.91 | 14.6 | 1.85 |
| 224 | 0.92 | 0.92 | 14.7 | 1.92 |
| Mean | 0.92 | 0.91 | 14.9 | 1.87 |
| CV | 1.99 | 2.54 | 5.04 | 9.59 |
| LSD05 | 0.01 | 0.02 | 0.77 | 0.18 |

In a similar study in corn (2017) increasing fertilizer-N applications did not change the yield (Olson et al., 2019). In the northern Great Plains, corn response to N rate studies consistently showed a quadratic response and the greatest yield increase per unit of applied N was greatest at lower yields (Franzen 2015).

## Grower Managed Trials

### Yield

Data from drones and yield monitors were collected from five wheat production fields in North Dakota and Minnesota in 2019. In each of these fields, N-rich and N-poor strips were included to increase the likelihood of being able to measure greater variability in yield and NDVI in these fields. Even though there was excessive moisture often during the season, wheat yields this season were comparable to the yields from previous wheat crop planted in the grower's rotation plan (Table 3). These yields are within the range of yields obtained in the counties, but generally below the trend line for yield the last five years according to the online National Agricultural Statistics Service (NASS). The wheat yields in the fields that were included in this research are likely lower than is the potential for the area due to late planting and excessive moisture at times during the season.

The average yields for the high, low, and farmer's rate fertilizer strips are shown in Table 4 along with the overall average for each of the fields monitored. Yields averaged over all the treatments within a farm ranged from 0.83 Mg $ha^{-1}$ in Breckenridge, MN (Wilkin County) to 2.33 Mg $ha^{-1}$ in East Grand Forks, MN (Polk County).

Table 3. Wheat yield (average and range of values) and past field wheat yields for the five wheat fields monitored in 2019. Data were from combined-mounted yield monitors. Years in parenthesis were the last year wheat was grown in this field.

| Location of field | Yield range in 2019 | Average yield of whole field 2019 | Yield from field when last grown (year) to wheat |
|---|---|---|---|
| | | ---(Mg $ha^{-1}$)--- | |
| Campbell, MN | 0.14-1.62 | 1.30 | 1.63 (2016) |
| Breckenridge, MN | 0.11-1.89 | 0.91 | 1.03 (2015) |
| Colfax, ND | 1.39-2.63 | 2.01 | 1.91 (2017) |
| Walcott, ND | 0.14-2.62 | 1.81 | 1.91 (2018) |
| East Grand Forks, MN | 1.38-2.98 | 2.29 | 2.42 (2013) |

Table 4. Average wheat yields from N-rich, N-poor and grower's rate strips, at five farms in North Dakota and Minnesota, 2019.

| Location | N-poor strip | N-rich strip | Growers Rate | Average of field |
|---|---|---|---|---|
| | | | --- (Mg $ha^{-1}$)--- | |
| Campbell, MN | 1.35 | 1.40 | 1.34 | 1.36 |
| Walcott, ND | 1.84 | 1.93 | 1.55 | 1.72 |
| Colfax, ND | 2.16 | 2.04 | 2.08 | 2.09 |
| Breckenridge, MN | 0.95 | 1.00 | 1.00 | 0.83 |
| East Grand Forks, MN | 2.14 | 2.53 | 2.33 | 2.33 |

Data from all five fields were collected and analyzed the same way. However, only the field maps from Campbell, MN are included in the thesis in order to give an example of how these maps were developed. Data from the other locations will be characterized and summarized in tables only.

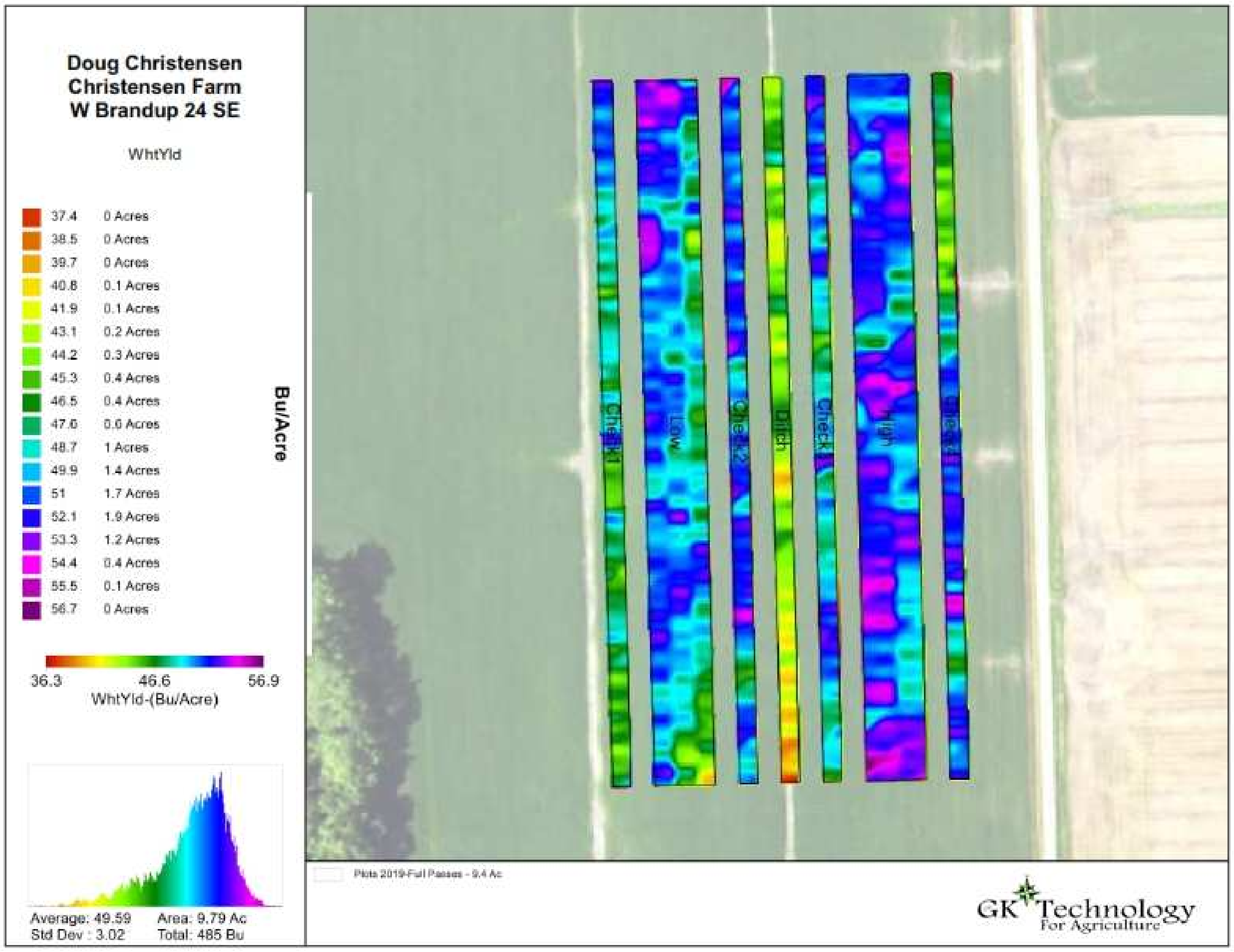


Figure 1. Yield monitor map for 2019 wheat field, with farmer rate, N-poor, N-rich strips and drainage ditch indicated in Campbell, MN.

Fields with the greatest variability are the ones that will benefit most from variable rate management practices. Though the farmers included in this study were located within the Red River Valley where soils are considered to be the most uniform in the state due to the limited slope and similar parent material. The greatest variability in yield between the N-rich strip and N-poor strip was in East Grand Forks, MN (Table 4). The N-rich strip yielded 0.39 Mg ha$^{-1}$ higher than the N-poor strip. This information suggests that adding more N to the field would likely increase yield. The other fields only showed an average of 0.06 Mg ha$^{-1}$ yield increase in the N-rich strip compared to the N-poor strip. There was one case in Colfax, ND (Table 4) where the N-poor strip yielded 0.12 Mg $ha^{-1}$ higher than the N-rich strip. The variability in yield within the field and between the strips with different N levels is graphically illustrated in Figure 1.

**Protein**

Three samples were taken from the high N rate strip, low N rate strip, and farmer's rate areas. Higher rates of N did not consistently result in higher protein levels, nor did lower rates of N result in lower protein level (Table 5). For some fields, this was the case, but not all. In Walcott, ND, the farmer rate and the N-rich rate significantly increase protein levels compare to the N-poor rate.

Table 5. Average grain protein level for the N-rich, N-poor, and farmers rate N strips in 2019.

| Location 2019 | N-Rich Rate | N-poor Rate | Farmers N Rate | LSD 0.05 |
|---|---|---|---|---|
| Campbell, MN | 11.5 | 11.9 | 12.3 | N/S |
| East Grand Forks, MN | 15.2 | 14.9 | 15.0 | N/S |
| Breckenridge, MN | 14.8 | 14.3 | 14.5 | N/S |
| Walcott, ND | 12.3 | 11.7 | 12.3 | 0.53 |
| Colfax, ND | 11.3 | 10.0 | 10.8 | N/S |

†N/S = not statistically different at the 0.05 level of significance.

**NDVI**

Nitrogen reference strips provide guidance to farmers to help prevent over-application or under-application of N fertilizer. These strips can help identify areas where plants have enough N or areas where soil N resources are insufficient and the addition of N could increase yield (Cornell, 2015). An N-rich strip is where extra N was applied to ensure sufficient N was applied so that N would not be limiting production. A strip of at least 100 feet long per representative area is ideal. It is important to avoid headlands, wet areas, or other problematic areas in the field when deciding where to place the N strips. Plant response in the N-rich strips is used as a basis to determine the maximum yield potential of the specific field for that year. A N-poor strip (or check) is a strip in the field where no N, or a reduced amount of fertilizer N is applied at planting and where readings will reflect the soil N supply capacity from past manure applications, rotation credits, and soil organic matter. It provides the yield potential if no further N fertilizer was added. If there are no visible differences between the N-rich and the N-poor or farmer applied rates reference strips, it indicates that soil levels of N are adequate for optimum yield and no N fertilizer addition is needed. On the other hand, if the plants in the N-rich area look much more advanced and healthier, it is clear in the N-poor strips that the available N is not sufficient for the crop to reach its full yield potential and side-dressing N is advised. In our study, we wanted to use the varied N-rate strips to induce variability that could provide insight into whether variable rate programs might be more efficient than the currently used, single N rate application of the farmers.

Table 6. Average and the range NDVI values from the N-poor, N-rich, and farmer's nitrogen rate at the 6-leaf, boot, and heading stage of wheat of sensing.

| Location | Crop Growth Stage | N-poor Rate | N- rich Rate | Growers N Rate | Range | Average |
|---|---|---|---|---|---|---|
| Campbell, MN | 6-Leaf | 0.92 | 0.93 | 0.93 | 0.63-0.94 | 0.79 |
| | Boot | 0.87 | 0.89 | 0.89 | 0.41-0.92 | 0.66 |
| | Head | 0.51 | 0.52 | 0.54 | 0.34-0.55 | 0.44 |
| Walcott, ND | 6-Leaf | 0.94 | 0.94 | 0.94 | 0.86-0.97 | 0.91 |
| | Boot | 0.54 | 0.57 | 0.56 | 0.48-0.56 | 0.52 |
| | Head | 0.53 | 0.53 | 0.53 | 0.48-0.57 | 0.53 |
| Colfax, ND | 6-Leaf | 0.94 | 0.93 | 0.94 | 0.70-0.95 | 0.82 |
| | Boot | 0.53 | 0.54 | 0.52 | 0.38-0.56 | 0.47 |
| | Head | 0.46 | 0.47 | 0.47 | 0.35-0.56 | 0.46 |
| Breckenridge, MN | 6-Leaf | 0.87 | 0.92 | 0.88 | 0.53-0.92 | 0.73 |
| | Boot | 0.92 | 0.91 | 0.92 | 0.74-0.94 | 0.84 |
| | Head | 0.52 | 0.53 | 0.52 | 0.41-0.54 | 0.48 |
| East Grand Forks, MN | 6-Leaf | 0.87 | 0.88 | 0.87 | 0.73-0.90 | 0.81 |
| | Head | 0.54 | 0.55 | 0.53 | 0.47-0.58 | 0.52 |
| Average | | 0.71 | 0.72 | 0.72 | | 0.64 |

NDVI varied within fields, between crop growth stages when data were collected, and with strips that varied in N rate (Figures 2-4).

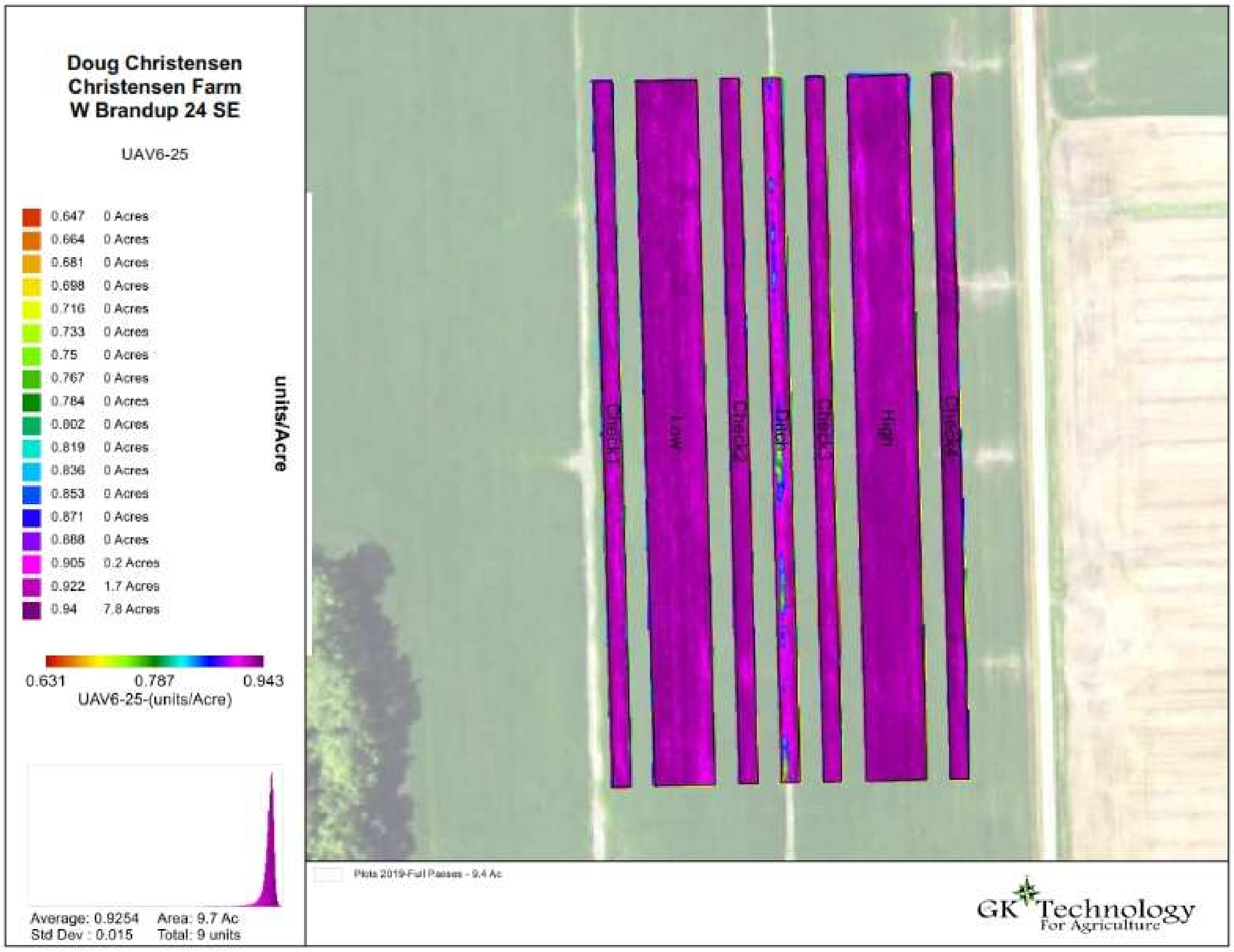


Figure 2. NDVI of N-rich, N-poor, and farmer applied N-rate strips at the 6-leaf stage of wheat in Campbell, MN 2019

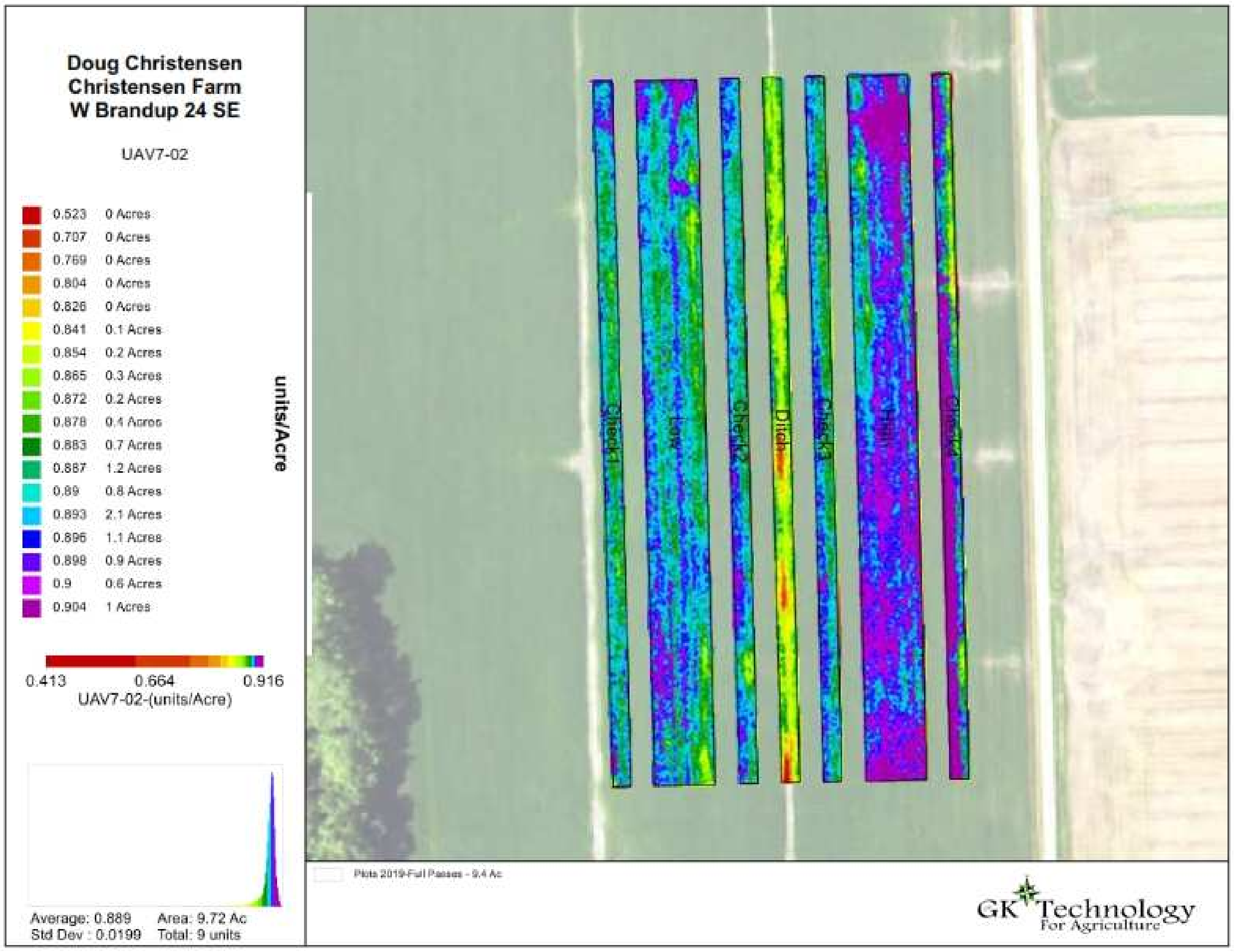


Figure 3. NDVI of N-rich, N-poor, and farmer applied N-rate at the boot stage of wheat in Campbell, MN 2019

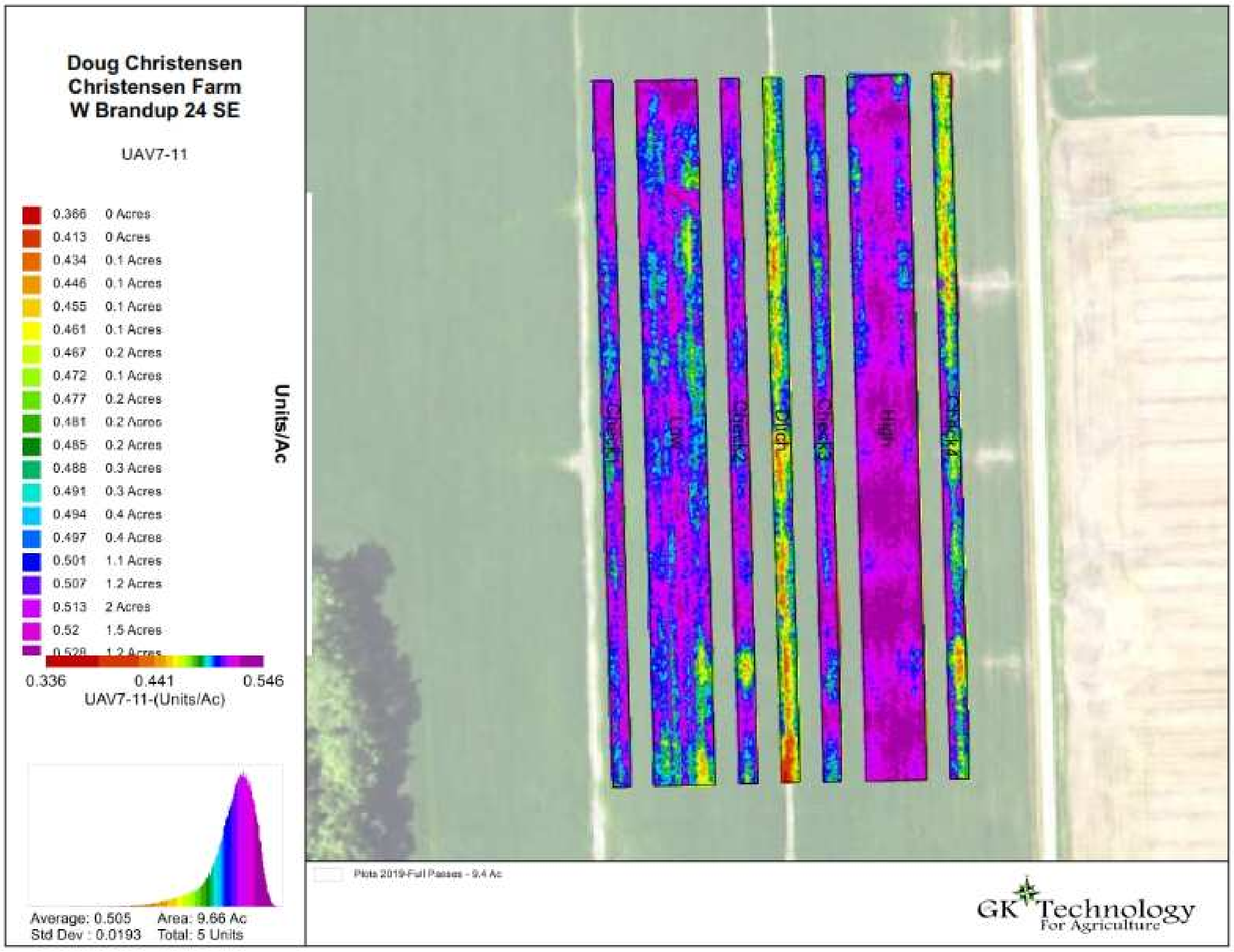


Figure 4. NDVI of N-rich, N-poor, and farmer applied N-rate at heading stage of wheat in Campbell, MN 2019.

There are similar results in our study and research done by others that monitoring NDVI values earlier in season for an early detection of nitrogen deficiency allows for a better prediction of yield. Guan et al. (2019) Found very good correlations between drone NDVI and yield in both wheat and rice, with the best timing near flowering. Similarly, with cotton, later stages were more predictive of N need (Ballester et al., 2017).

## Correlations

In order to quantify the value of NDVI collected from drone mounted sensors and NDVI collected from satellite imagery that was available from public sources, correlation analysis between these variables and the georeferenced yield data collected by farmers during the harvest of 2019 was performed. The correlation matrixes were developed from output from EZAnalyze tool that is used by the GK Technology software that was used for generating prescription maps. The correlation matrixes contain only r values but not statistical probabilities. Given the very large number of values that were used to calculate these correlations (not estimated, but many thousands) no level of significance was indicated. Given the very large number of values used, most if not all the r values in the following tables would be considered statistically significant. The fact that they are statistically significant, however, does not mean that these values have a practical significance. The larger the correlation coefficient, the more the relationship between the two variables is explained. A correlation of less than 0.3 would be considered very weak, a correlation between 0.3 and 0.5 is considered “weak,” a correlation between 0.5 and 0.7 is considered “moderate,” and a correlation greater than 0.7 is considered to be quite strong. In the following correlation matrixes, wheat yield was derived from the yield data collected by the yield monitor. These data were provided by the grower from his combine. Data points were converted to image files with the GK software at one-meter resolution. NDVI obtained from the UAV were collected at 0.08-meter resolution. The 8 cm data was resampled back to 3 meters, outliers were trimmed, and resampled back to a 1-meter resolution. The All merged zones variable was calculated by combining Landsat (30-meter satellite imagery) and the Sentinel (10 meter satellite imagery) collected from these fields from 2008 through 2017. Only NDVI values greater than 0.35 were used in these averages. Images were interpolated to 3 meters (default resolution of software) and merged using an Equalize/Normalize equation. Images use were from any crop other than soybeans, as Iron Clorosis and Cyst Nematodes that are common issues in the Red River Valley, were known to greatly impact NDVI values. The 2018 data was configured the same way. The Sentinel (10-meter satellite imagery) was merged together from only 2018 images with NDVI values greater than a 0.35 average. Images were interpolated to 3 meter (default resolution of software) and merged using an Equalize/Normalize equation.

Table 7. Correlation coefficients between various variables and wheat yield in 2019, Breckenridge, MN farm location.

| Variable name | Wheat Yield 2019 | NDVI from UAV 6-25 | NDVI from UAV 7-2 | NDVI from UAV 7-11 | Merged zones† | N app. ‡ | Corn 18 zones § |
|---|---|---|---|---|---|---|---|
| Wheat yield | - | -0.29 | -0.21 | -0.17 | -0.44 | -0.47 | -0.44 |
| UAV 6-25 | -0.29 | - | 0.54 | 0.45 | 0.45 | 0.39 | 0.45 |
| UAV 7-2 | -0.21 | 0.54 | - | 0.52 | 0.48 | 0.44 | 0.48 |
| UAV 7-11 | -0.17 | 0.45 | 0.52 | - | 0.58 | 0.5 | 0.58 |
| Merged zones | -0.44 | 0.45 | 0.48 | 0.58 | - | 0.89 | - |
| N app. | -0.47 | 0.39 | 0.44 | 0.50 | 0.89 | - | 0.89 |
| Corn 18 zones | -0.44 | 0.45 | 0.48 | 0.58 | - | 0.89 | - |

†Merged zones is a composite of NDVI values collected from several satellite images over the past few season, irrespective of crop.

‡N app is the N rate map developed from merged zone data using GK mapping software

§ Corn 18 zones are N application zones derived from NDVI values from satellite images collected in the previous corn crop grown on this field (in 2018).

At the Breckenridge location (Table 7) the variables exhibited a negative correlation with yield in 2019. This was the only field were NDVI and NDVI exhibited correlations that were opposite of what is normally expected. Why higher NDVI values would predict lower yields is not understood unless there were some factors that impacted the crop's growth after these data were collected, like lodging or severe disease development that was more pronounced in the more favorable parts of the field. NDVI values from the three different dates were moderately correlated with each other. NDVI collected from drone-based sensors was moderately correlated with merged zones (NDVI from several satellite images collected over several seasons) and corn 18 zones (NDVI from satellite images collected from the corn crop grown in 2018), with the last data collected being the most strongly correlated of the UAV collected NDVI than the earliest collected data, suggesting that data collected later in the season is better able to detect difference in crop performance than earlier data.

Table 8. Correlation coefficients between various variables and wheat yield in 2019 farm location in Walcott, ND

| Variable Name | Wheat Yield 2019 | NDVI from UAV 6-25 | NDVI from UAV 7-2 | NDVI from UAV 7-11 | Merged zones† | N app. ‡ | 18 soy zones§ |
|---|---|---|---|---|---|---|---|
| Wheat yield | - | 0.28 | 0.22 | 0.11 | 0.10 | 0.19 | -0.10 |
| UAV 6-25 | 0.28 | - | 0.64 | 0.45 | 0.23 | 0.31 | 0.31 |
| UAV 7-2 | 0.22 | 0.64 | - | 0.52 | 0.27 | 0.38 | 0.31 |
| UAV 7-11 | 0.11 | 0.45 | 0.52 | - | 0.21 | 0.27 | 0.19 |
| Merged zones | 0.10 | 0.23 | 0.27 | 0.21 | - | 0.83 | 0.42 |
| N app. | 0.19 | 0.30 | 0.38 | 0.27 | 0.83 | - | 0.61 |
| 18 soy zones | -0.10 | 0.32 | 0.31 | 0.19 | 0.42 | 0.61 | - |

†Merged zones is a composite of NDVI values collected from several satellite images over the past few season, irrespective of crop.

‡N app is the N rate map developed from merged zone data using GK mapping software

§ Soy 18 zones are N application zones derived from NDVI values from satellite images collected in the previous corn crop grown on this field (in 2018).

At the Walcott location (Table 8), correlations coefficients between drone-based NDVI values and wheat yield decreased and were less predictive of yield the later in the season that they were collected. The later flights were poorly predictive of wheat yield. Even given the poor predictability of the UA-based NDVI values, they were more predictive than merged zones and the soybean 2018 zones. In fact, the limited correlation between the soybean zones and yield was also negative, indicating that higher NDVI values in the soybean in 2018 predicted a lower yield for wheat in 2019. It is not obvious what might have been the reason for this negative relationship.

Table 9. Correlation coefficients between various variables and wheat yield in 2019 farm location in East Grand Forks, MN

| Variable Name | Wheat Yield 2019 | NDVI from UAV 6-25 | NDVI from UAV 7-11 | Merged zones† | N app. ‡ | 18 soy zones§ |
|---|---|---|---|---|---|---|
| Wheat yield | - | 0.05 | 0.24 | 0.18 | 0.12 | -0.08 |
| UAV 6-25 | 0.05 | - | 0.25 | 0.19 | 0.27 | 0.08 |
| UAV 7-11 | 0.24 | 0.28 | - | 0.37 | 0.39 | 0.08 |
| Merged zones | 0.18 | 0.21 | 0.38 | - | 0.90 | 0.27 |
| N app. | 0.12 | 0.25 | 0.38 | 0.90 | - | 0.39 |
| 18 soy zones | -0.08 | 0.08 | 0.08 | 0.27 | 0.39 | - |

†Merged zones is a composite of NDVI values collected from several satellite images over the past few season, irrespective of crop.

‡N app is the N rate map developed from merged zone data using GK mapping software

§ Soy 18 zones are N application zones derived from NDVI values from satellite images collected in the previous corn crop grown on this field (in 2018).

At the East Grand Forks location (Table 9), correlations coefficients between drone-based NDVI values and wheat yield increased and were more predictive of yield the later in the season that they were collected. Since the NDVI from the last date was the most strongly correlated with yield, these data suggest that NDVI collected later in the season is better able to detect differences that affect yield than earlier in the season. The UA-based NDVI values, were more predictive than merged zones and the soybean 2018 zones. The NDVI values in East Grand Forks, MN were much less predictive of yield than Campbell, MN (Table 11). In fact, the coefficients were about half those we observed in Campbell, MN. Nevertheless, these values were consistently positive unlike those at Breckenridge, MN (Table 7).

Table 10. Correlation coefficients between various variables and wheat yield in 2019 farm location in Colfax, ND

| Variable Name | Wheat Yield 2019 | NDVI from UAV 6-25 | NDVI from UAV 7-2 | NDVI from UAV 7-11 | Merged zones | N app. | 18 soy zones |
|---|---|---|---|---|---|---|---|
| Wheat yield | - | 0.42 | 0.47 | 0.47 | 0.36 | 0.31 | 0.29 |
| UAV 6-25 | 0.42 | - | 0.61 | 0.56 | 0.33 | 0.33 | 0.37 |
| UAV 7-2 | 0.47 | 0.61 | - | 0.66 | 0.43 | 0.40 | 0.43 |
| UAV 7-11 | 0.47 | 0.56 | 0.66 | - | 0.82 | 0.79 | 0.48 |
| Merged zones | 0.36 | 0.33 | 0.43 | 0.82 | - | 0.95 | 0.49 |
| N app. | 0.31 | 0.34 | 0.40 | 0.79 | 0.95 | - | 0.49 |
| 18 soy zones | 0.29 | 0.37 | 0.42 | 0.49 | 0.49 | 0.49 | - |

†Merged zones is a composite of NDVI values collected from several satellite images over the past few season, irrespective of crop.

‡N app is the N rate map developed from merged zone data using GK mapping software

§ Soy 18 zones are N application zones derived from NDVI values from satellite images collected in the previous corn crop grown on this field (in 2018).

At the Colfax location (Table 10), correlations coefficients between drone-based NDVI values and wheat yield increased and were more predictive later in the season. However, this field showed that NDVI values became stagnant from 7-2-2019 to 7-11-2019. UA-based NDVI values, they were more predictive than merged zones and the soybean 2018 zones. This location presents the strongest correlations values of any other location. The results were quite similar to the Campbell location (Table 11) and there were much stronger correlations between NDVI, and yield compared to East Grand Forks. Of the five fields included, four of the five had positive correlations, two were weak, and two moderate.

Table 11. Correlation coefficients between various variables and wheat yield in 2019 farm location in Campbell, MN

| Variable name | Wheat Yield 2019 | NDVI from UAV 6-25 | NDVI from UAV 7-2 | NDVI from UAV 7-11 | Merged zones† | N app. ‡ | Soy 18 zones§ |
|---|---|---|---|---|---|---|---|
| Wheat yield | - | 0.41 | 0.55 | 0.62 | 0.47 | 0.45 | 0.39 |
| UAV 6-25 | 0.41 | - | 0.77 | 0.50 | 0.21 | 0.19 | 0.18 |
| UAV 7-2 | 0.55 | 0.77 | - | 0.60 | 0.32 | 0.28 | 0.25 |
| UAV 7-11 | 0.62 | 0.49 | 0.60 | - | 0.36 | 0.33 | 0.35 |
| Merged zones | 0.47 | 0.21 | 0.32 | 0.36 | - | 0.93 | 0.50 |
| N app. | 0.45 | 0.19 | 0.28 | 0.34 | 0.93 | - | 0.44 |
| Soy 18 zones | 0.39 | 0.18 | 0.25 | 0.35 | 0.50 | 0.44 | - |

†Merged zones is a composite of NDVI values collected from several satellite images over the past few season, irrespective of crop.

‡N app is the N rate map developed from merged zone data using GK mapping software

§ Soy 18 zones are N application zones derived from NDVI values from satellite images collected in the previous corn crop grown on this field (in 2018).

At Campbell, MN drone-based NDVI values were moderately predictive of wheat yield in the 2019 season. Furthermore, NDVI values became more predictive as the season progressed. The late season NDVI values from the drone were more predictive than the merged zones (merged together from 2008 through 2017 imaged with NDVI values greater than 0.35 average) and the NDVI values obtained from satellite imagery from the soybean crop in 2018. The NDVI values from the first date was highly correlated with the data from the second date, but only modestly correlated with the NDVI collected on the last date. Since the NDVI from the last date was the most strongly correlated with yield, these data suggest that NDVI collected later in the season is better able to detect differences that affect yield than data collected earlier in the season. This seems logical, as factors that will likely impact yield will be more manifest as the season progresses (there are more chances nitrogen and water availability to impact a crop the longer it is growing, as an example). Nevertheless, one challenge with NDVI is that it tends to saturate after full canopy closure and others have found it difficult to detect differences in crop yield after canopy closure. As was noted in the earlier section, NDVI values tended to decrease as the season progress (rather than saturate and remain stable). Differences in NDVI values collected from a drone-based sensor can be due to a number of factors, such as angle of sun at the time of the flight, haze, and presence of spikes, etc. since these data are based on passive reflectance (unlike the GreenSeeker or Crop Circle that collect NDVI reflectance from an active light source).

In order to look at the relationship between NDVI and yield at Campbell, MN, data from the yield map and UAV maps were broken up into 140 cells using GK Technology. Each cell holds an average yield and NDVI value for that particular location of the field. The graph indicates NDVI being most predictive later in the season. The slope is stronger than the other two graphs and shows a strong linear equation. When expressed as an exponential equation, there was little difference compared to the linear equation. The grouping on all three equations is strongly noticeable with the grouping occurring with higher NDVI and yield. Based upon the R squared value, NDVI is not a perfect indicator of yield, but on certain fields, NDVI could be a useful tool in predicting yield.

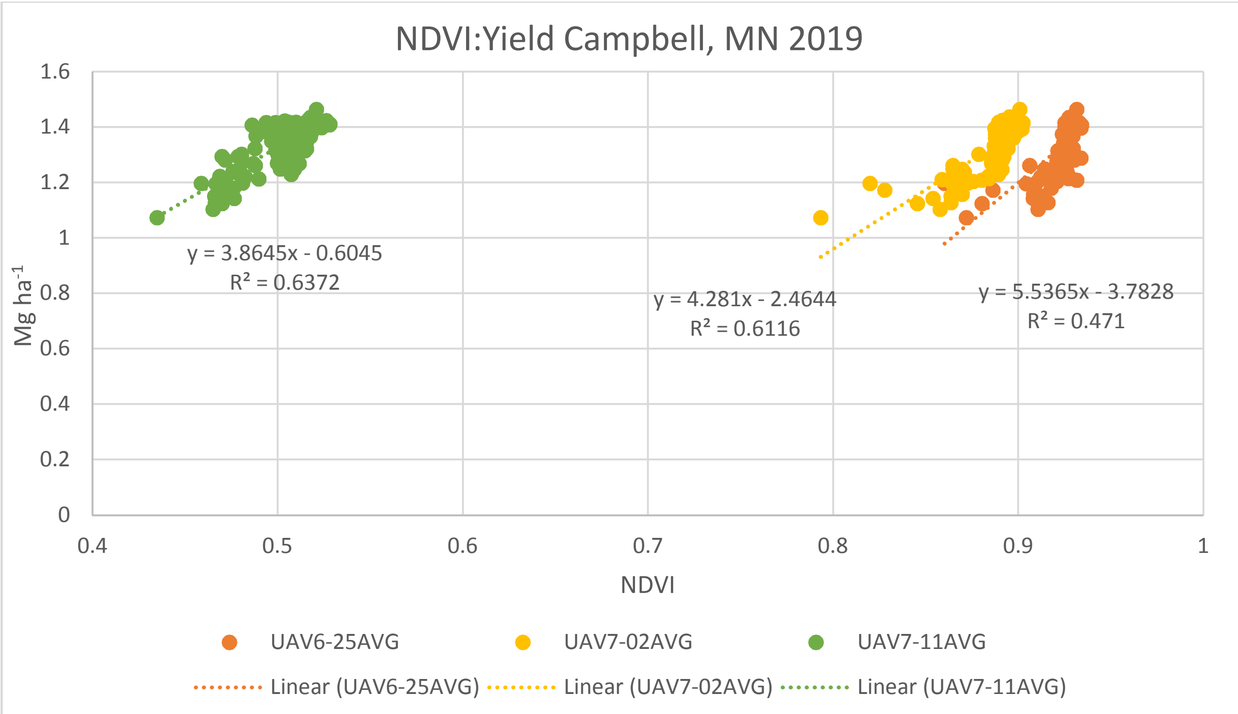


Figure 5. NDVI to yield correlation in Campbell, MN.

Overall, majority of the grower's fields showed the last data collected being most strongly correlated of the UAV collected NDVI than the earliest collected data. This suggests that data collected later in the season is better able to detect difference in crop performance than earlier data. This is likely due to factors that impact a crop the longer it is growing such as N and water availability. There were different responses at different locations, which is to be expected. Perhaps if this study were to be extended, taking soil conditions into account would be helpful in understanding why such differences occurred. At this time, we can say that the differences occurred due to geographical differences, weather conditions including heavy moisture, and the fields ability to hold adequate N. NDVI was not always predictive of yield. Unfortunately, many of the values were considered "weak" correlations. Breckenridge, MN had the poorest correlations and Colfax, ND presented the strongest correlations.

## Conclusions

The purpose of the small plot research was to determine if we could detect differences in NDVI when N level varied in a smaller and controlled area. In this study we did not find any response of NDVI to added N in the small plots. In 2019, increasing the N rate from 0 to 44 kg $ha^{-1}$ resulted in an increase in yield, unlike 2018, where yield increased up to the 89 kg rate (Table 1 and 2). Therefore, we were unsuccessful as there was no significant correlation between NDVI and yield or NDVI and protein. The data suggests that NDVI was saturated and therefore could not distinguish the plots that would ultimately have different yields and protein levels. Planting was delayed in 2019 and Bacterial Leaf Streak was problematic. These both could be factors limiting the response of NDVI, yield and protein and resulting in limited or no correlation between the traits.

In the grower managed study, N strips were used to introduce more variability in yield and NDVI in order to determine if sufficient variability can be obtained to allow potential variable rate N prescriptions. The N-rich, N-poor, and grower's rate of N did not consistently differ in yield, protein and NDVI. NDVI for the whole field was the greatest early on in the growing season and dropped significantly later season. Generally, the varied N strips were not consistently helpful in determining N adequacy as they only infrequently differed from the farmer's rate of fertilizer for any of the traits measured.

In the correlation graphs, we did find NDVI could assist in predicting yield. As stated in the literature and based off of this study, NDVI values at this point in time would not "solely" be useful in developing N prescription maps. Most growers will likely plant a different crop following wheat, therefore making it difficult to use a drone map from a single year to create the prescription. Crop rotation, previous year's NDVI, yield maps, and potentially soil maps are all components necessary to create the most accurate prescription map. Based off of the results from figure five, NDVI is approximately 60% predictive of yield. It would be up to the grower's preference if 60% is a strong enough value to use NDVI to predict yield.

Overall, we concluded that there are cases where yield can be predicted with NDVI from a drone. Four out of five fields showed consistency that the best time to collect NDVI is later in the growing season. Additional research is needed to determine factors that affect the predictions of yield by NDVI in different environments.

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## APPENDIX

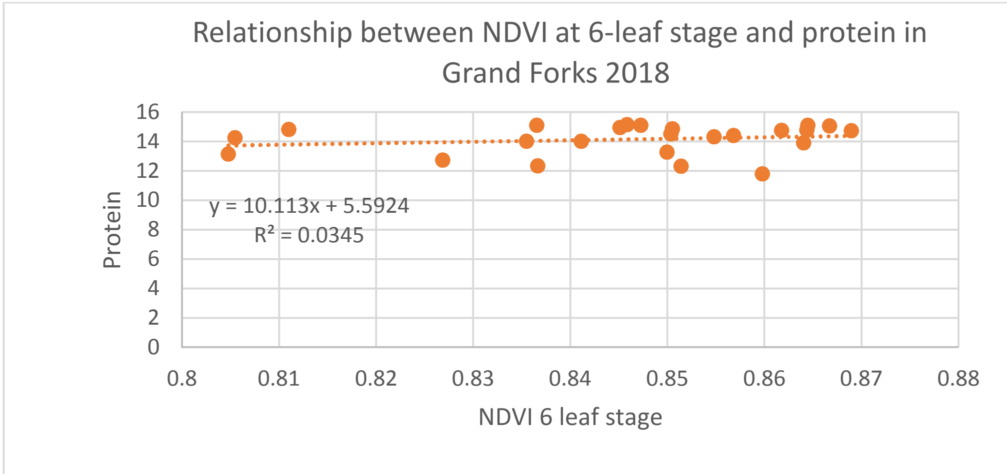


Figure A1. Relationship between NDVI at 6-leaf stage and protein in Grand Forks 2018

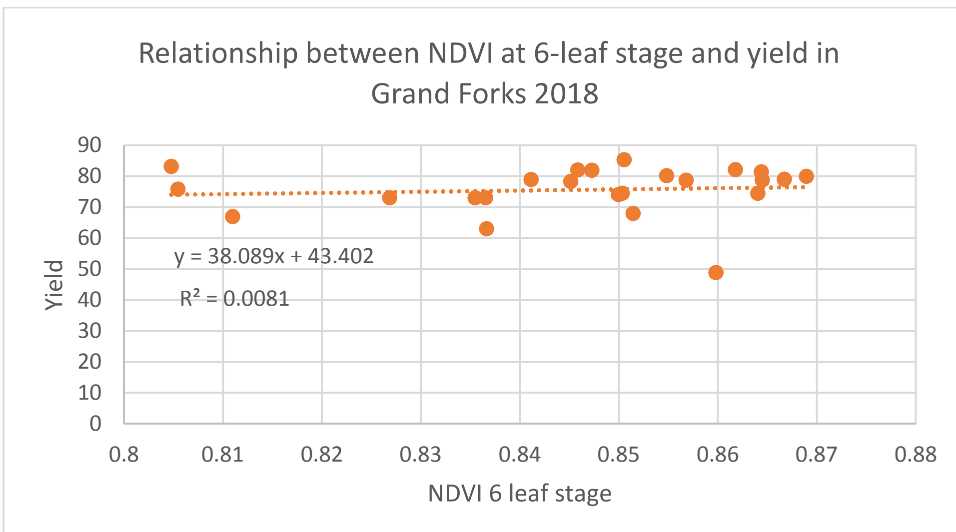


Figure A2. Relationship between NDVI at 6-leaf stage and yield in Grand Forks 2018

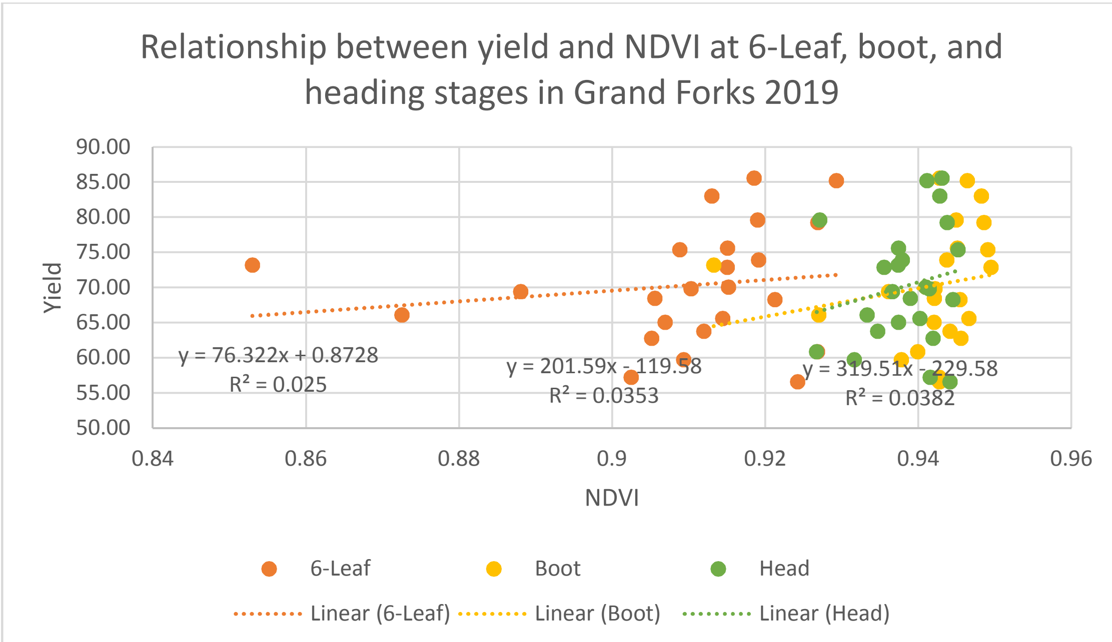


Figure A3. Relationship between yield and NDVI at 6-leaf, boot, and heading stages in Grand Forks 2019

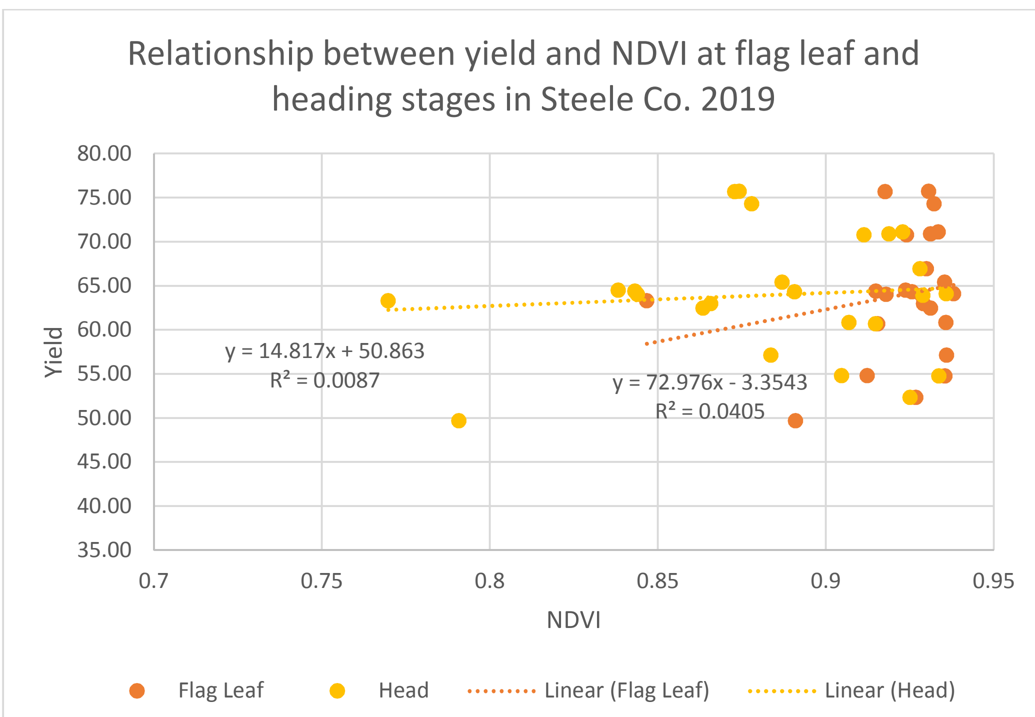


Figure A4. Relationship between yield and NDVI at flag leaf and heading stages in Steele Co. 2019

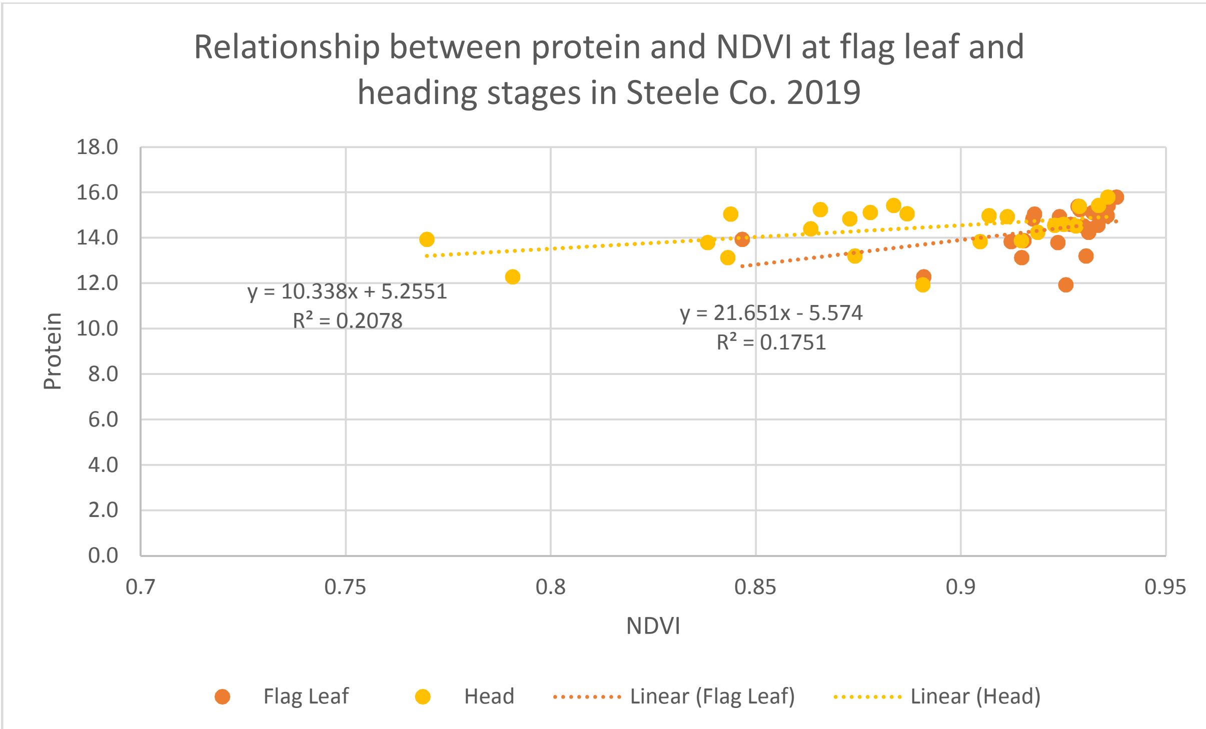


Figure A5. Relationship between protein and NDVI at flag leaf and heading stages in Steele Co. 2019

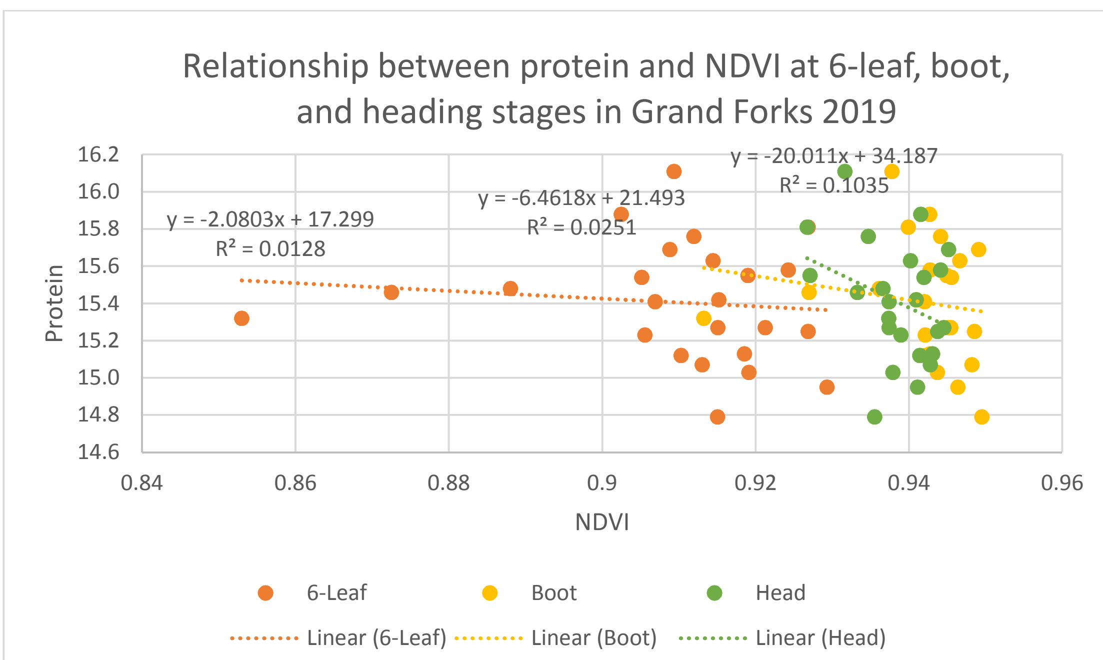


Figure A6. Relationship between protein and NDVI at 6-leaf, boot, and heading stages in Grand Forks 2019