ON THE PROFITABILITY OF UAS-BASED NDVI IMAGERY FOR VARIABLE RATE NITROGEN PRESCRIPTIONS IN CORN AND WHEAT IN NORTH DAKOTA

A Thesis
Submitted to the Graduate Faculty
of the
North Dakota State University
of Agriculture and Applied Science

By

Christopher Joseph Duchsherer

In Partial Fulfillment of the Requirements
for the Degree of
MASTER OF SCIENCE

Major Department:
Agribusiness and Applied Economics

March 2018

Fargo, North Dakota

North Dakota State University
Graduate School

Title

On the Profitability of UAS-Based NDVI Imagery for Variable Rate Nitrogen Prescriptions in Corn and Wheat in North Dakota

By

Christopher Joseph Duchsherer

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

SUPERVISORY COMMITTEE:

David Roberts
Chair

Dragan Miljkovic

John Nowatzki

William Wilson

Approved:

March 26, 2018	William Nganje
Date	Department Chair

ABSTRACT

This study examines the grower's decision to invest in precision agriculture technologies especially in-season variable rate nitrogen applications based on NDVI data collected from UAVs. NDVI, yield, soil, and other field data were collected from multiple corn and wheat fields located throughout North Dakota. Each field was divided into management zones to determine profitability of utilizing the technology based on in-season nitrogen applications for the grower's field practice, high, low, and no applications. Results show that using the NDVI data collected from UAVs can be profitable when the grower decides to make the decision to apply nitrogen in a sidedress application.

Keywords: NDVI, UAS, variable rate, sidedress, nitrogen

ACKNOWLEDGEMENTS

This thesis is long overdue and because of this fact, I have some people to acknowledge who have been helpful in getting me to finish.

Amy, my wife: I know that this has been something that you have wanted me to finish for a very long time and it has been bothering you for some time, but now it is finished. I appreciate all the help, prayers, and support you have given me to make this a reality. I look forward to spending many more years with you and seeing you grow in your own endeavors and seeing our family grow.

Dr. Roberts, my advisor: I thank you for taking me on in the middle of your project to work on this thesis with you. I know that it has taken time away from some of your own projects that you need to complete. I appreciate our meetings and our discussions about various topics related to agriculture, the world, and anything else that might have come up over the last eighteen months. I also thank you for helping me to make this thesis a reality; without an advisor like you, I'm guessing this would have never happened.

My committee members, Dr. Miljkovic, John Nowatzki, M. S., and Dr. Wilson. I appreciate your help in this process. Dr. Miljkovic, I wish that I would have had more time to have some conversations with you about my topic, econometrics, and economics in general. I'm sure that you could have given me even more advice than what I have already received from you. John, thank you for providing insight into precision agriculture and drones in agriculture. Your thoughts about the industry always gave me issues and topics to ponder and have helped me improve the knowledge I am transferring to my students. Lastly, Dr. Wilson, I appreciate your help in this thesis as well. I also thank you for any of the other assistance you have given me when it comes to networking opportunities in the industry.

The members of the Agribusiness and Applied Economics Department at NDSU: I thank you for teaching me new ways to think about the things of this world. This Master's program has helped me and still impacts how I think about economic issues and agriculture. I know that I could have never gotten to where I am without your help.

My fellow graduate students and work colleagues: I thank you for helping me learn about other places in the world. When I started this Master's program, I didn't realize how much more there was to agriculture and the world than just the things I knew in North Dakota. I will always remember you and wish to catchup with you someday.

Mary, Joseph, Francis, Thomas, and Therese, thank you for your prayers.

Lastly, to any other people I may have forgotten, thank you.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

1. STATEMENT OF PROBLEM

1.1. Introduction

A Food and Agriculture Organization of the United Nations (FAO) publication reported that "just satisfying the expected food and feed demand will require a substantial increase in global food production of 70 percent by 2050" (FAO, 2009, p. 8). Natural resources, mainly land, used in agriculture production are being degraded by soil nutrient depletion, erosion, desertification, and depletion of freshwater reserves to name a few (FAO, 2009). The need for technological options for increasing food production including new plant varieties adapted for varying conditions, farming systems with improved labor and water saving technologies, reduction of losses and waste in production, and natural resource management is growing (FAO, 2009). These few items mentioned are the exact reason precision agriculture is becoming the norm in agricultural production in the United States.

Precision agriculture is a very hard term to define because if you ask any number of people, they would probably give you a wide variety of different answers. For the purposes of this study, the definition we will use is the one used by the United States Department of Agriculture as defined by Searcy (1997):

> Precision farming is a management strategy that employs detailed, site-specific information to precisely manage production inputs. This concept is sometimes called precision agriculture, prescription farming, or site-specific management. The idea is to know the soil and crop characteristics unique to each part of the field, and to optimize the production inputs within small portions of the field. The philosophy behind precision agriculture is that production inputs (seed, fertilizer,

> chemicals, etc.) should be applied only as needed and where needed for the most economic production. (p. 1)

Since one of the main goals of precision agriculture is applying inputs where needed, farmers' production costs should be reduced, but the goal of reducing costs can only be done with new technologies being researched and released today.

Precision agriculture can also be described in other ways, as mentioned above. Specifically, looking at precision agriculture through an economic lens gives us a similar, but slightly different spin on how precision agriculture technology should be applied in the world. As defined by Mulla, "precision agriculture generally involves better management of farm inputs such as fertilizers, herbicides, seed, fuel (used during tillage, planting, spraying, etc.) by doing the right management practice at the right place and the right time" (2013, p. 358). This "better management" translates into producers working to maximizing the output from the land while minimizing input costs.

Another key about precision agriculture is to think about precision agriculture in the terms of the growers who are using the technologies. Most farmers are not economists; they do not always fit into one risk tendency, which makes it difficult to model their decisions. Some growers will focus on maximizing their yields in the field rather than profit. These growers are less likely to adopt technologies based on their financial advantage to their operation, but whether the technology will give them something to talk about with other growers or something that might be fun for them to use on their operation. Overall, most growers will focus on the profitability of a technology before they adopt.

1.2. Technologies Important to Precision Agriculture

Thinking about the philosophy behind precision agriculture of only applying production inputs as needed, we need to break down the various technologies and how they are useful. These technologies include gathering data to make the determination of how many inputs need to be applied in a certain spot in the field, determining where a piece of equipment is located in the field, and applying the proper amount of inputs in a particular spot in the field.

The first technologies vital in allowing producers to determine where they are located in the field are the availability and implementation of GPS systems, both for guidance and data recording. On the data recording side, GPS systems allow a producer to mark a location or determine their exact location in a field, or in other words, georeferencing. Guidance systems help reduce operator fatigue because operators do not have to focus on keeping machinery driving straight and reduce overlap, but the main reason for its importance in this study is so that operators can use multiple precision agriculture systems at once (Schimmelpfenning, 2016). These precision agriculture systems can run and control customized seeding rates and application rates of fertilizers and pesticides.

The second technology allowing producers to utilize precision agriculture is Variable-Rate Technology (VRT). VRT is a combination of a number of different pieces of equipment and controls that make variable-rate applications in fields with seed, chemicals, fertilizers, and other inputs. Schimmelpfennig (2016) explains VRT the following way:

> Customized seeding and application of fertilizer, chemicals, and pesticides is accomplished with machinery attachments that can vary the rate of application from GPS controls in the cabs of tractors. Geolocated data from yield and soil maps or from guidance systems can be used to preprogram application equipment

> to apply desired levels of inputs or to seed at pre-determined rates at different locations in a farmer's field. Controllers adjust the levels of inputs coming from each nozzle or feeder on command from a computer program that uses the geo-referenced data points. (p. 4)

This VRT can take information from yield maps, field imagery, soil tests results, soil map zones, or any other source of data to create a georeferenced map of target application rates for each particular spot in the field. These maps are considered prescription maps in the world of precision agriculture. The equipment that controls machinery in the cab will also produce a map after the operation has occurred with the actual amount of product that was applied in each area of the field; these maps are known as as-applied maps.

The last technology needed for precision agriculture is related to determining how many inputs to apply on a certain spot in a field. These technologies vary widely depending upon the time of the growing season when the data needs to be collected. One technology used prior to planting is georeferenced soil sample sites to determine inputs needed in a number of areas in a field. During the growing season, the main method of determining the crop progress and yield potential is through remote sensing. Remote sensing is the use of instruments to collect data from and about objects without having to make any physical contact with those objects (Ortiz, Shaw, & Fulton, 2011). Remote sensors are mounted on a variety of different platforms including satellites, airplanes, unmanned aerial systems (UAS) or drones, farm machinery, or hand-held devices each with their own advantages and disadvantages. Technology used at harvest time includes yield and moisture monitors that gather data to create yield maps for analysis. These different technologies can be used in combination or on their own to determine proper placements of inputs within a field.

Two specific technologies that will be addressed in this document include drones and remote sensing. Unmanned aerial systems (UAS, e.g., drones) are aircraft that can be flown remotely via various systems and software. UASs have been historically employed in use by the military (Gago et al., 2015). One reason UASs have not gained more popularity with civilian populations is that aviation regulations for UASs were not clear until recent years (Turner, Kenkel, Holcomb, & Amall, 2016). Since the clarification of UAS aviation regulations, UASs have become more popular among civilians for hobby use, inspection, and agricultural purposes (Gago et al., 2015, Turner, Kenkel, Holcomb, & Amall, 2016). More items relating to drones and their limitations and capabilities will be discussed in Chapter Two.

The data that is collected from remote sensing from satellites or drones can be used to calculate a Normalized Difference Vegetation Index (NDVI) rating. NDVI is an index that is used to determine the vigor of plant life. When plants are actively growing, they are able to absorb light from the red and blue sides of the visible light spectrum. However, near-infrared (NIR) light is reflected while plants are growing. The measurement of the red and near infrared light are then used to calculate the NDVI (Rouse Jr., Haas, Schell, & Deering, 1974). Even though other methods of computing vegetation indices exist, NDVI has been the method most commonly used in the industry due to the ease of calculation (Food Security and Nutrition Analysis Unit, n.d.; Liu & Huete, 1995). NDVI has been used in a variety of applications including field variability (Tucker, Holben, Elgin Jr., & McMurtrey III, 1979), yield estimation in an assortment of crops (e.g., Badu, 2016; Fortes, Prieto, Garcìa-Martìn, Còrdoba, Martinez, & Campillo, 2015; Haung, Wang, Li, Tian, & Pan, 2013), and insect and disease management in crops (Bharathkumar & Mohammed-Aslam, 2015; Estel, Kuemmerle, Alcántara, Levers, Prishchepov, & Hostert, 2015; Mulla, 2013; Sruthi & Mohammed-Aslam, 2015; Tong et al., 2017; Viña, Gitelson, Rundquist, Keydan, Leavitt, & Schepers, 2004).

1.3. Problem Statement and Elements of the Problem

Most producers engaged in precision agriculture will employ at least one of the above technologies. The main question for producers is to determine whether each particular technology adopted on the farm will be profitable. One such technology is drone-based remote sensing. Because drone technology is a costly investment for agricultural producers, it is important that the benefits to the producer outweigh the risk of investment. Thus, this paper examines the usefulness of drone-based remote sensing technologies for estimating yield, and determining if in-season fertilizer application are needed.

1.4. Objectives

The objectives of this study are twofold. The first objective is to determine if drone-based remote sensing technology can be used effectively to determine nutrient needs for plants during the growing season. The second objective is to determine the usefulness of drone-based remote sensing technology in determining plant health and yields later in the season.

1.5. Hypothesis

It is expected that UAS capabilities and sensor technologies will be useful in determining where to apply inputs in a precision agriculture program. The technologies, as available, should be able to identify and help determine if action is needed to reduce nutrient deficiencies during the growing season.

1.6. Organization

Chapter Two will discuss UAS capabilities and sensor technologies. In addition, previous literature relating to precision agriculture, remote sensing, UAS, and other elements related to the objectives of the study. Chapter Three will provide a theoretical construct of the model used in this study. Chapter Four will also introduce the data used to produce the findings and cover results and sensitivities. Chapter Five will cover implications, limitations, and the conclusion.

2. LITERATURE REVIEW

Precision agriculture is a topic that has been well studied in economic, agronomic, and engineering disciplines (Legg & Stafford, 1998; Mulla, 2013; Nowatzki & Hoffman, 2009; Searcy, 1997). Since site-specific farming is relatively new in agriculture, and not all questions about it have been answered, research will continue in the near future especially as new technologies are developed and adopted in agricultural settings. The following chapter contains information on the decisions and economics related to adopting precision agriculture technologies. The main focus will be on the use of remote sensing, NDVI, and UAS.

2.1. Precision Agriculture

The economic and environmental aspects of crop production can be improved by using precision agriculture techniques (Searcy, 1997). While environmental concerns are becoming more prominent in society, improving economic sustainability is the main reason producers use precision agriculture in their operations. Precision agriculture encompasses many different facets, some of which will be discussed in this section.

2.1.1. History of Precision Agriculture

Even hundreds of years ago, farmers were able to identify that variability existed within their fields (Colewell, 1956; Turner, Kenkel, Holcomb, & Amall, 2016). Accounting for this variability was only taken into account when applying agricultural practices in recent history. One of the first precision agriculture practices developed was custom prescribed tillage, which involves changing the tillage practices within the field based on soil type (Johnson, Schafer, & Young, 1983). A process of identifying nutrient deficiencies through the use of grid soil sampling and aerial imagery was later developed in the mid-1980’s by the company Soil Teq (Fairchild, 1988). This practice was the beginning of site-specific farming. Although site-specific farming allowed farmers and agronomists to begin the process of managing variability within the field, the necessary technologies to make the identification of locations of variability in the field possible were not readily available in agriculture. GPS technology was the first technology that was needed to begin the precision agriculture revolution.

When Soil Teq began, GPS was only being used for government purposes. It wasn't until the early 1990's when the satellite network neared completion and the technology became more reliable that consumers were able to purchase GPS receivers (Stafford & Ambler, 1994). Because GPS allows agricultural producers to identify the spatial coordinates of trouble spots (e.g., variability, weed patches, wet spots, etc.) in a field, it provides the basic building blocks needed to begin site-specific farming practices. Some precision agriculture practices that have become commonplace because of GPS are georeferenced soil sampling, remote sensing, yield mapping, and variable rate application of crop inputs including pesticides, fertilizers, and other soil amendments (Jones, Fleming, Pavuluri, Alley, Reiter, & Thomason, 2015; Mulla, 2013; Stafford, 2000). Using these practices together "can provide a guideline to farmers to achieve high yield in spatial patterns" (Bharathkumar & Mohammed-Aslam, 2015, p. 1404). For this reason, Searcy (1997) refers to GPS as the "heart of precision agriculture" (p. 1).

Another technology that was made more useful because of GPS is yield monitoring, which also was developing during the early 1990's. Yield monitoring is measuring the flow of grain as it is harvested. Using yielding monitoring in conjunction with GPS allows for the calculation of yields in smaller sections of a field (Mulla, 2013). With this data, producers are able to create yield maps (Vansichen & de Baerdemaeker, 1991; Searcy, Schueller, Bae, Borgelt, & Stout, 1989; Stafford, Ambler, & Smith, 1991). Yield maps give a visual representation of variability within a field, which ultimately allow producers to identify areas of similar production ability. These areas can be combined into clusters of similar production, which are then used to create management zones (Mulla, 2013). Once management zones are created, inputs can be applied according the needs of these zones in differing rates.

Variable rate technology (VRT) allows producers to customize the application rate for different crop inputs throughout a field. The application equipment can be programed using data from sources such as yield and soil maps to ensure that the appropriate amount of input is being applied to each location of a field (Schimmelpfenning, 2016). Maps used to set input levels are called prescription maps, and as-applied maps (i.e., maps printed with the amount of applied product) are created post application.

VRT has also allowed for numerous other technological developments in precision agriculture related to applying fertilizer and spraying. Some of the first technologies were section control, automatic flow control, and variable speed motors (Nowatzki & Hofman, 2009). These technologies allowed for the development of technology where sections automatically turn off when the area has already had an application, automatic row shutoffs in seeding applications, and even individual nozzle control where each nozzle will shutoff when it crosses an area where application has already occurred (Raven Industries, n.d.). One of the more common uses of VRT is for nitrogen application in the field where there is variability and where the crop has the greatest need for the nitrogen application (Ruffo, Bollero, Bullock, & Bullock, 2006). These new advances have become increasingly available in the last decade and help meet needs in environmental concerns and help producers manage fields at smaller scales (Stafford, 2000).

The last technology important to a precision agriculture system is the use of geographic information systems (GIS). These systems are used to combine all of the data collected from yield maps, remote sensing, soil test results, as-applied maps, prescription maps, and so forth in one platform (Andrade-Sanchez & Heun, 2010). This allows the producer or a consultant to make decisions in the field based on the variability in different regions. Several different GIS platforms are available, but some have specifically been designed for use in agriculture applications (e.g., SMS, FarmWorks, Climate FieldView).

GPS, yield monitoring and mapping, VRT, and other technologies have developed in the last few decades with improvements to design, efficiency, and accuracy. The next section will discuss the current state of precision agriculture.

2.1.2. Current State of Precision Agriculture

The improvements in technology over the past years have refined the processes of precision agriculture. Because georeferenced information has been collected for a number of years, the focus in precision agriculture is now starting to use this information spatially and temporally to make management decisions (Mamo, Malzer, Mulla, Huggins, & Strock, 2003; Miao, Mulla, Randall, Vetsch, & Vintila, 2009; Mulla, 2013; Varvel, Wilhelm, Shanahan, & Schepers, 2007). Including data not only in spatial reference, but with temporal references, allows individuals using precision agriculture to determine how the variability of the field changes over the course of time and to make better management decisions. For instance, if an area of the field produces high yields each year over a variety of crops, it can be inferred that this area is a high producing area and then can be managed in a different manner. Collecting abundant data poses unique challenges, especially for the agriculture industry.

One of the major challenges of today is handling the amount of data required for precision agriculture systems. While computer technologies have increased, so has the amount of data needed in order to verify that a management zone has been created properly. This has lead to the need for a major amount of storage for this data, but producers are sometimes concerned with the sharing of their personal production data and field history for various reasons including the unwillingness to share their data with other people and security or third party use of their production data (Ireland-Otto, Ciampitti, Blanks, Burton Jr., Balthazor, 2016). In some cases, the fear over big data has caused individual producers to purchase their own data processing software to manage their own crop plans and management zones (Ireland-Otto et al., 2016). This can have multiple negative implications because producers may not be up to date on the cutting edge of precision agriculture and agronomic concepts which results in the loss of information required from big data to help determine future management decisions.

The current use of data on farms has also created the desire to have more timely information. In the past, data were typically available well after the data collection operation was completed; however, advances in technology allow producers to collect data throughout the growing season in a relatively quick manner (Mulla, 2013). As an example, yield data can be uploaded to a site or software system and can be analyzed immediately after harvest. This data can now be analyzed to not only show that variation exists in the field, but also make decisions on what caused variability in the field (Simelli & Tsagaris, 2015).

The last question that needs to be addressed is how much precision agriculture technologies are being used in agriculture today. This data primarily comes from two surveys: one of crop input suppliers from Purdue and the other from producers conducted by the USDA. The Purdue data collected in 2015 noted that over 80% of input suppliers were offering at least some precision agriculture services and were using GPS guidance with auto-control and auto-steer (Erickson & Widmar, 2015). Nearly 70% of those suppliers also have VRT capabilities, but the numbers begin to drop off significantly when it comes to dealing with data. Only 40% of dealers are working with growers to conduct analysis of their data.

The study from the USDA Agricultural Resource Management Survey (ARMS) was conducted on different years for different crops, but the results show similar trends (Schimmelpfennig, 2016). Nearly 70% of all acres of corn and soybeans in the United States are harvested with a combine that has a yield monitor, but only about half of that data is ever translated into a yield map. VRT use also shows similar trends as the yield mapping with approximately one-third of the acres produced in corn and soybeans being used with those technologies. Larson, Roberts, English, Cochran, & Wilson (2005) proposes that the individuals who are not adopting these technologies are lacking the computer skills to adopt the technologies. While adoption rates of precision agriculture vary depending upon the technology type employed, the future of precision agriculture will no doubt require technology developers to make the technology more user-friendly, which will aid in its use (Gago et al., 2015). Additionally, many producers are hesitant to adopt the technologies on their own farm because the efficacy of these concepts is still largely unproven (Stafford, 2000).

2.1.3. Future of Precision Agriculture

Even though precision agriculture adoption rates are typically not very high, early adopters are acquiring knowledge that will support development of new technologies in the future and help producers make better decisions (Schimmelpfennig & Ebel, 2016). Some of the knowledge gained is related to user friendliness of the technology for even the less tech-savvy users, which is translating into industry developing their products in a way that is user friendly (Gago et al., 2015). Overall, Stafford (2000) proposes that

> precision agriculture is seen to be the correct way ahead for crop producers… because crop production is more precise, because inputs are optimized leading to

> reduced costs and environmental impact and provides the audit trail that consumers and legislation increasingly require. (p. 269)

Ultimately, the goal of precision agriculture would be not to only manage variability of some smaller spatial zone, but for each plant individually (Stafford, 2000). However, the challenge of targeting individual plants lies in the current unavailability of technology and data processing capacity for multiple channels of real-time sensor data (Mulla, 2013). Additionally, the need for more precise application techniques is in high demand. For example, Stafford (2000) notes, “The conventional spinning disc fertilizer spreader… can hardly be described as precise” (p. 271). Still, the technology available today has come a long way from times when precision agriculture focused on tillage based on soil types.

2.2. Remote Sensing and NDVI

Remote sensing is defined as using “instruments… to collect data from and about objects without having to make physical contact with them” (Ortiz, Shaw, & Fulton, 2011, p. 1). The following sections will cover a history of remote sensing and talk more about one primary method of using remote sensing in agriculture, especially the Normalized Difference Vegetation Index (NDVI). Legg and Stafford (1998) suggested that because the plant itself is best at determining what it needs, then remote sensing would be very beneficial if it could determine what the crop is ‘saying’ and help determine where to place the inputs the crops needs (Stafford, 2000). Industry is trying to understand what the crops are ‘saying’ because they have adopted remote sensing technologies at about 50% use rate, although companies selling remote sensing might be driven by trying to buy more grain from the producer or sell more crop inputs meaning adoption rates may be higher than if growers adopted on their own (Erickson & Widmar, 2015).

2.2.1. Satellite Based Remote Sensing

Once the first satellites were launched in the late 1950s and 1960s, scientists on Earth began to get pictures back of the world and started noticing the changes in the coloration of the planet as the seasons changed. This lead to the launch of the Landsat 1 satellite in 1972 with sensors that collected green, red and two infrared bands of light with 80m resolution every eighteen days (Mulla, 2013). Bauer and Cipra (1973) used this imagery to determine where corn and soybean fields were located in the US and did so with 83% accuracy. Around this same time, scientists at NASA were developing models to determine vegetation density (Tucker, 1978; Tucker et al., 1979). Over the course of time, satellite resolution became smaller and smaller down to meter accuracy; passes occur nearly daily and even more spectral bands are available for use, but there are some problems with satellite sensing (Mulla, 2013).

One of the biggest problems with satellite imagery is the inability to account for the atmosphere, which can reduce the imagery quality (Mkhabela, Bullock, Raj, Wang, & Yang, 2011). Some of these interferences might include cloud cover, haze, or other air quality detractors. This disturbance can cause issues in the timeliness of imagery obtained for making management decisions (Steven, 1993). Additionally, satellite imagery can also have high costs associated with getting the right data at the right time. Costs tend to increase as the resolution decreases making most satellite imagery resolution between 2.5 and 30 meters. However, some of these issues can be overcome when remote sensors are mounted on aircraft.

2.2.2. Aerial Mounted Remote Sensors

Remote sensors can also be mounted on aircraft, which alleviates some of the issues from satellite-based imagery. Since these sensors are mounted on vehicles like planes and unmanned aerial systems, they can be deployed when atmospheric concerns are minimal, but this comes with a time factor limitation (Mulla, 2013). Aircraft are not set in specific patterns like an orbit for a satellite, so aerial imagery needs to be planned in advance.

Other limitations that can be overcome with aerial imagery is that the resolution of the images can be very small. One sensor available on the market today can collect images down to centimeter resolution with a low flight elevation (Parrot SA, 2017a). This data is useful in determining where agronomists should focus their energy if they are trying to improve yield for the producer. Additional information on remote sensing with UAS will be discussed later in this chapter.

2.2.3. NDVI

NDVI is a tool that has been available in agriculture since the 1970s. Scientists realized that there was a ‘green wave effect’ when the grasses in the Great Plains began growing in the spring (Rouse Jr. et al., 1974). Further research lead to the development of an index that showed the vegetative growth that was occurring in plants using data from the Landsat 1 satellite (Mulla, 2013).

Around the same time, research was being conducted in plants determining how to measure the amount of chlorophyll in the plant. This research lead to the determination of reflectance characteristics of plants in the various bands of the electromagnetic spectrum. Research was conducted by NASA (Tucker, 1978; Tucker et al.,1979) using the various electromagnetic bands and determined that the red and near-infrared (NIR) bands of light were the most useful in determining vegetative growth in plants. The red band measured light from the 0.63-0.69 μm and the NIR band of light measured in the 0.75-0.80 μm spectral frequencies (Tucker, 1978). All of this seems a little scientific, so it might be easier to explain using agronomic terms.

The idea behind the reflectance index is really quite simple and is shown in Figure 2.1 and Figure 2.2. During the process of photosynthesis, the plant chlorophyll absorbs red and blue light from the electromagnetic spectrum; when a plant is actively growing (i.e., more green), more blue and red light is absorbed (Liu & Huete, 1995; Tucker, 1978). NIR light is scattered by the plant leaves into the plant canopy and is not readily absorbed in actively growing vegetation (Food Security and Nutrition Analysis Unit, n.d.; Gago et al., 2015; Liu & Huete, 1995; Tucker, 1978). NIR is also sensitive to dead or non-photosynthetically active vegetation because more of the light escapes from the canopy than is absorbed (Tucker, 1978). All of this leads to the following index (Rouse Jr. et al., 1974):

$$NDVI = \frac{NIR - Red}{NIR + Red} \qquad \text{(Eq. 2.1)}$$

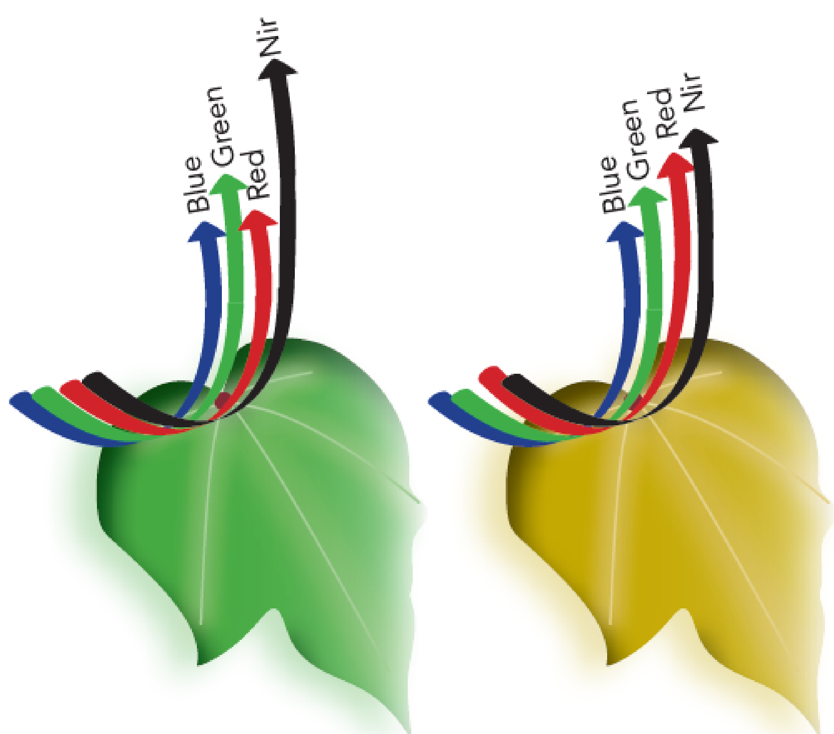


Figure 2.1. Differences in Reflected Light Between Healthy and Unhealthy Leaves
Source: Ortiz, Shaw, & Fulton, 2011.

The research of Rouse Jr. et al. (1974) specifically noted other combinations correlated with vegetation, but this version gives a value indicative of vegetation. The normalization procedure completed by the denominator portion of the equation works to eliminate some of the variability in the vegetative index by normalizing the value (Rouse Jr. et al., 1974). Ultimately, it was found that stronger green color in vegetation could be linked to yield and crop condition (Raun, Solie, Johnson, Stone, Lukina, Thomason, et al., 2001; Tucker et al., 1979).

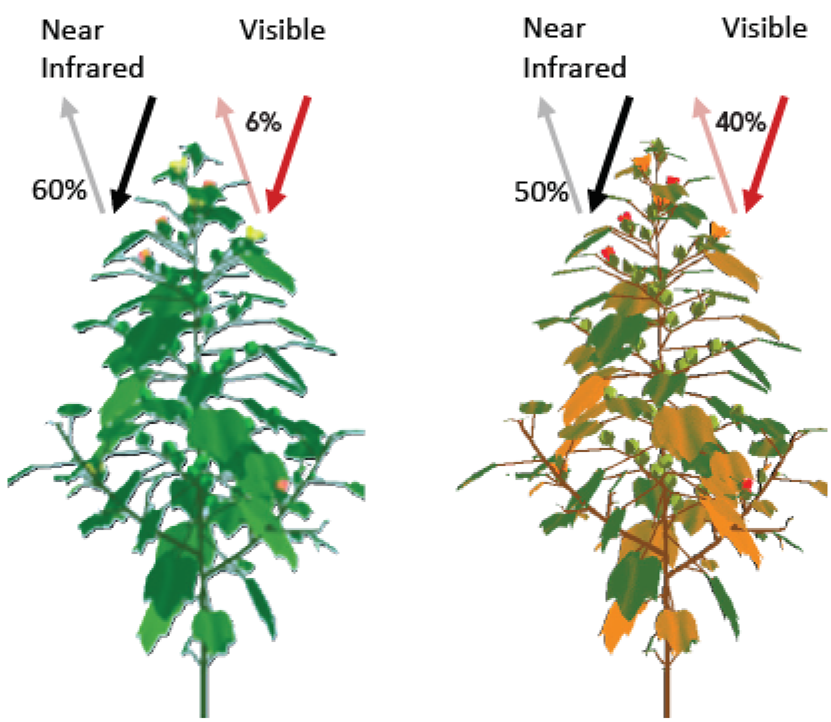


Figure 2.2. Differences in NDVI Based on Plant Health Status
Source: Ortiz, Shaw, & Fulton, 2011.

Early research in this area also investigated several other indices with the NDVI measurement becoming the primary standard for imagery analysis (Tucker, 1978; Tucker et al., 1979). Although many vegetation indices exist, the NDVI is the most commonly used because of its simplicity and efficiency (Food Security and Nutrition Analysis Unit, n.d.; Liu and Huete, 1995). Even today, new indices are still being proposed to estimate vegetation and ultimately yield (Gago et al., 2015; Mulla, 2013; Sruthi & Mohammed-Aslam, 2015; Viña et al., 2004).

Some studies of NDVI also show the potential of using NDVI to estimate yield. One of the first pioneering studies using NDVI to estimate yield noted that NDVI explained at least 60% of field variability (Tucker et al., 1979). Other, more recent studies used NDVI to estimate yields after a flood and estimate the crop yield loss (Shrestha, Di, Yu, Kang, Yuan-zheng, & Yu-qi, 2017), drought stress and NDVI related to yield (Mekliche, Hanifi-Mekliche, Aïdaoui, Gate, Bouthier, & Monneveux, 2015; Sruthi & Mohammed-Aslam, 2015), tomato yield estimation (Fortes et al., 2015), yield forecasts in the Canadian Prairies (Mkhabela et al., 2011), estimating yield of rice (Haung et al., 2013), and estimating sugarbeet yield (Badu, 2016). Other key uses of NDVI include the following: understanding Nitrogen fertilizer update and making Nitrogen fertilizer recommendations (Magney, Eitel, & Vierling, 2017; Roberts, Brorsen, Solie, & Raun, 2013), and estimating wheat protein and N-uptake (Magney, Eitel, Huggins, & Vierling, 2016). NDVI has also been used in a wide variety of other applications including insect and disease management, water stress indication, crop nutrient needs, weed infestations, phonological development of plants, pasture performance, changes in cropping patterns, and even rainforest deforestation (Bharathkumar & Mohammed-Aslam, 2015; Estel et al., 2015; Mulla, 2013; Sruthi & Mohammed-Aslam, 2015; Tong et al., 2017; Viña et al., 2004). With over 144,000 hits on a Google Scholar search, the applications of NDVI are too numerous to mention in further detail.

With all of these studies using NDVI, it would make sense to think that NDVI should be used in all circumstances, but this might not be the case. Berg noted at the 2017 Precision Ag Summit in Jamestown, North Dakota that NDVI is the most used and abused technology in precision agriculture today. NDVI does have some drawbacks and as noted above, many different vegetation indices are available for use. None of these major indices are necessarily the best in all cases, but some might be better in specific cases (Sruthi & Mohammed-Aslam, 2015).

For instance, one study found that changes in soil and atmospheric conditions could cause vegetation to change; these interactions are very complex and might not be able to be easily compensated for in a vegetative index (Liu & Huete, 1995). Some other limitations are noted in a variety of studies.

Specific limitations of NDVI are numerous, which makes determining the situations when NDVI technology is appropriate even more important. For example, changes in the atmospheric conditions could have an impact on NDVI values (Liu & Huete, 1995; Pereira, Casaroli, Vellame, Alves Jr., Evangelista, 2016). Additionally, research has not fully determined optimal operating scenarios for remote sensing equipment to provide consistent and replicable data (Crusoil et al., 2017). Background noise from soil reflectance may also cause NDVI to miss changes in the vegetation when plants are maturing (Mulla, 2013). Also relating to soil reflectance, recommendations for Nitrogen fertilizer application from NDVI might vary depending upon the soil moisture and soil types (Jones et al., 2015; Liu & Huete, 1995). Other studies found the optimal timing for sensing crops was early in the morning and that NDVI changes during the day based on plant growth processes, but always sensing at the same time is not always possible in crop production applications (Crusiol et al, 2017; Zhang, Lan, Pute, & Wenting, 2014). Lastly, NDVI used for yield estimates don't always account for yield loss that occurs after the growing season or last sensing date (Mkhabela et al., 2011).

Some other concerns are related to the equipment needed to determine NDVI. One study found there were no adequate methods to make sure that all equipment used in calculating NDVI were gathering reliable data that could be replicated under similar conditions (Fan & Liu, 2017). Many remote sensors will gather data on different light bands that cause NDVI values to fluctuate. Lastly, using the NDVI for practical purposes requires special knowledge and proficiency that most crop producers might not have (Ireland-Otto et al., 2016). Overall, NDVI in combination with other agronomic indicators and data may help obtain better results when using NDVI for any study purpose (Bharathkumar & Mohammed-Aslam, 2015; Sruthi & Mohammed-Aslam, 2015; Stafford, 2000; Tucker et al., 1979).

2.3. Unmanned Aerial Systems

Unmanned aerial systems (UAS) have been known by a number of different names over the past years. Previously, these were referred to as Unmanned Aerial Vehicles (UAVs), or more commonly drones (Mazza, 2015). The move from the UAV designation to UAS designation was mainly due to the fact that drones or UAS do not only comprise the vehicle itself, but also the systems relating to the operation of the vehicle. This section of the paper will discuss the various different types of UAS, some capabilities, regulations, among others.

2.3.1. UAS Background

Historically, drones have been used in military applications and were primarily designed for reconnaissance or use as targets (Gago et al., 2015). Recently, drones have been used for other civilian purposes including hobby, entertainment, inspection, and agriculture (Gago et al., 2015; Turner et al., 2016). These drones have a big advantage over other aircraft because they can be operated manually through a wireless connection by remote control or be pre-programmed to fly in a specific pattern based on GPS (Simelli & Tsagaris, 2015).

UAS need a variety of different pieces of equipment to operate and to fly safely. These parts are related to the control system of the drone and can contain “GPS waypoint navigation with altitude and airspeed, fully-integrated multi-axis gyroscopes and accelometers, GPS systems, pressure indicators and meters, [and] pressure airspeed sensors… mounted on hardware circuit boards” (Simelli & Tsagaris, 2015, p. 731). Most drones have the capabilities to land and take off on their own and will return to the takeoff position if, for some reason, communication is broken off between the operator and the drone itself or if other issues occur during flight (Simelli & Tsagaris, 2015).

Drones typically have the ability to change positions within flight relatively easily, which is due to its construction using lightweight composite materials (Simelli & Tsagaris, 2015). The lightweight construction gives the drones the abilities to fly at high and low altitudes easily, which can be an advantage when it is being used in commercial applications (Gago et al., 2015; Simelli & Tsagaris, 2015). Additionally, the cost of drones are expected to decrease as technologies are developed including more cost effective ways to manufacture the components, more companies begin producing drones, more services related to drones are offered, and as technology is shared between companies since most technology within this space is open sourced (Gago et al., 2015; Ireland-Otto et al., 2016).

2.3.2. UAS Capabilities

Drones are typically limited by a few different factors: flight duration, payload capacity, ability to fly in a variety of weather conditions, and specific use requirements (Simelli & Tsagaris, 2015). The varied needs of drone operations have led to countless different sizes, abilities, and autonomy levels in drone configurations (Simelli & Tsagaris, 2015). Some of these issues and configurations will be discussed below.

There are two main types of drones used commercially, especially in agriculture, in the UAS space today: fixed-wing and helicopter or multirotor (Ireland-Otto et al., 2016, Gago et al., 2015). Typically, fixed-wing drones have longer flight ranges and battery life than multirotor drones, but their ability to fly in all circumstances and perform certain functions maybe limited (Ireland-Otto et al., 2016). Four drone models used in agriculture are the DJI Phantom 4, DJI

Matrice 600 Pro, Sensefly eBee, and AgEagle RX60. The relevant information related to this study will be summarized in Table 2.1. Fixed-wing drones are typically used to collect data in larger areas due to their ability to fly faster and longer, but copter-type drones can fly in any direction, have the ability to hover in one location easily, and do not require much space for take-off or landing (Gago et al., 2015).

These drones are typically used with at least one remote sensor and have been used extensively in agriculture for remote sensing purposes, primarily because “they fly at lower altitudes, increasing images’ spatial resolution and they cost less, allowing for higher monitoring frequencies” than other aerial or satellite based remote sensing methods (Gago et al., 2015, p. 18). This allows for higher quality imagery than other remote sensing methods (Turner et al., 2016). Some of these different sensors include RGB (Red, Green, Blue), infrared, and thermal cameras (Simelli & Tsagaris, 2015).

Table 2.1. Comparison of Various Drones Used in the Agriculture Industry

	Phantom 4	**Matrice 600 Pro**	**Sensefly eBee**	**AgEagle RX60**
Type	Quadcopter	6 Rotor Copter	Fixed Wing	Fixed Wing
Flight Time	approx. 30 minutes	approx. 35 minutes	50 minutes	60 minutes
Size	14 inches diagonally	66 inches diagonally	38 inch wingspan	54 inch wingspan
Weight	3 pounds	22 pounds	1.5 lbs	7 lbs
Flight Speed	up to 45 mph	up to 40 mph	25 mph cruising speed, up to 55 mph	33 mph cruising speed, up to 50 mph
Payload Capacity	1 lb	12 lbs	1 lb	2.5 lbs
Special Features	Object Avoidance	Retractable Landing Gear, Easy Switching Between Payloads, Sub-Inch Location Accuracy with RTK	Multi-Drone Operation, Constructed out of Foam and Composite Materials	Constructed of Aircraft Grade Carbon Fiber Materials, Pre-Programmed Automatic Flight, Pre-Integrated with Agriculture Camera for NDVI

Sources: DJI, 2017a; DJI, 2017b; Sensefly, 2017; AgEagle Aerial Systems, 2016

Three of the more common sensors being used today in agriculture include the Parrot Sequoia, MicaSense RedEdge, and Sentera High Precision Single Sensors. Each of these different sensors are detailed in Table 2.2. Some of the specific features that are important when looking at sensors include how many and what bands are being collected per shot, resolution per pixel, light sensor availability, and the weight of the device. Being able to collect data from different bands give the operator the option to look at a wider range of vegetation indices. Resolution is important because it is a measure of how much information is stored in each pixel. For instance, if a sensor has a resolution of eight-centimeters, each pixel will collect a box eight square centimeters in size verses a sensor with ten-meter resolution, which would have a box ten square meters in size. It is important to also consider light sensors, which sense the change in brightness at the time of the shot and will then be able to make account for variability in brightness when making comparisons (Nguy-Robertson, Buckley, Suyker, & Awada, 2016). The light sensor will help eliminate the difference in the light reflectance values the camera picks up when the sun goes behind a cloud. Lastly, weight is an important factor because the lower the weight, the longer the drone will be able to fly before needing to return for another battery (Avanzini, de Angelis, & Giulietti, 2016).

Table 2.2. Comparison of Various UAS Sensors Used in the Agriculture Industry

	Sequoia	**RedEdge-M**	**High Precision NDVI or NDRE**
Brand	Parrot	MicaSense	Sentera
Color Bands	Green, Red, Red Edge, Near Infrared	Blue, Green, Red, Red Edge, Near Infrared	Red, Near Infrared
RGB	Yes	Yes	Yes, when used in conjunction with another sensor
Resolution at 400'	13 cm per pixel	8 cm per pixel	11 cm per pixel
Light Sensor	Included	Included	Optional
Weight	135 grams	180 grams	30 grams

Sources: Parrot SA, 2017b; MicaSense, 2017; Sentera, 2017a

2.3.3. UAS Regulations

Drones are relatively new to agriculture and to industry in general in the United States. Prior to 2012, there was a lack of regulations related to drones used for commercial purposes and where exactly they could be flown (Turner et al., 2016). The regulation process was started in 2012 when Congress passed the Federal Aviation Administration (FAA) Modernization and Reform Act (Ireland-Otto et al., 2016). This act contained laws that “mandated the safe and expedient integration of UAS’ into the National Airspace System (NAS) and the establishment of rules for the use of small UAS” (Ireland-Otto et al., p. 131). The rules made it clear on what the rules were for each class of drone use: recreational, commercial, educational, and government (Know Before You Fly, 2017c). For commercial and government uses, the FAA came out with Part 107 rules in June 2016, and these rules became active on August 29, 2016 (Know Before You Fly, 2017a; Know Before You Fly, 2017d). Educational flight rules are essentially the same as the recreational use requirements as long as the drone is not being used for research purposes and limited assistance in flying the drone is used by the instructor (Know Before You Fly, 2017b).

The classifications for FAA purposes are very simple. A recreational user of a drone is one who is flying for “fun” and does not intend to profit in any manner from the use of the drone (Know Before You Fly, 2017e). Commercial use of drones includes any instance when a business is operating a drone or if the operator has the intent of profiting from using the drone (Know Before You Fly, 2017a). Commercial operators of drones are required to follow rules stated in the Part 107, which will be discussed in later in this section. Government operators of drones can follow Part 107 rules or can apply for a blanket Certification of Authorization (COA) (Know Before You Fly, 2017d).

One of the most important pieces of regulation relating to drones is that all small drones weighing between .55 lbs and 55 lbs and used in commercial or government operations must register with the FAA (2017). The FAA makes it very simple to register each drone by entering in the drone's information into the FAA registration website and paying the $5 fee to register the aircraft. After completing this process, an FAA registration number is issued and must be displayed on the aircraft (FAA 2017).

The FAA (2016) also clarified the rules to operation of drones for commercial uses. The most important rules relating to drone operations are listed below:

- Drones must weigh a maximum of 55 lbs.
- The drone pilot must be in view of the drone at all times during operations without using anything other than corrective eyewear.
- Drones cannot operate over people not associated with its operation, within a building, tents, a covered structure, or in a vehicle.
- Drones must only be flown in daylight, otherwise special lighting is needed.
- Drones must yield to other aircraft.
- Drones cannot fly higher than 400 feet above ground level or faster than 100 mph.
- Drones must be inspected before flight to ensure safe operation.
- All payloads must be securely attached and the drone must still be able to be controlled.

The FAA (2016) also clarified the rules for operators or pilots of drones for commercial uses. The pilot must qualify and hold a remote pilot airman certificate, which requires passing a test on general aeronautical information, being screened by the TSA, and meeting the minimum age requirement of 16 years of age.

2.3.4. Other UAS Information

Technology for drones is quickly advancing allowing for many other uses of drones within agriculture, and the Association of Unmanned Vehicle Systems International estimates the uses of drones in agriculture to be 80% of the market in the United States (Jenkins & Vasigh, 2013; Turner et al., 2016). Drones in agriculture have been used for a wide variety of purposes, primarily focusing around remote sensing, but also for other uses. Drones have been used to identify areas that need herbicide applications where the issues cannot be identified from the ground (e.g., in the tall canopy of a corn crop), help with breeding by identifying desired plant traits, determine the differences in the field between what is the crop and what is a weed, identify where irrigation systems have not provided consistent results, and improve crop scouting efficiency to name a few (Gago et al., 2015; Louargant, Villette, Jones, Vigneau, Paoli, & Gée, 2017; Sugiura, Noguchi, & Ishii, 2005; Turner et al., 2016). While drones have many uses, a study conducted of Oklahoma agricultural cooperative managers revealed that there are still some individuals who doubt of the usefulness of drones in agriculture (Turner et al., 2016). Surprisingly enough, even though their knowledge about drones was very minimal, the cooperative managers still seemed eager to use the technology if it could help their business (Turner et al., 2016).

Lastly, drones used for different purposes are only beneficial if the data they collect is useful in some manner. Gago et al. (2015) outlines a workflow process for conducting any type of analysis with drones beginning with the research design, the data collection aspect, data processing, and finally the results or analysis stage. So far, this paper has primarily talked about the data collection aspect, but some of the most important portions of this entire process are with the data collection and analysis. In order for the information to be useful to researchers or producers, proper analysis needs to be completed before it is useful in making farm management decisions (Simelli & Tsagaris, 2015). One study of cotton farmers found that farmers are not very likely to adopt drone technologies unless they had a consultant who was using the service or there was a web-based service available to process the data so that the producer could act on the information (Larson et al., 2005). Without someone with good knowledge of how this technology can be applied and how to correctly interpret the data, the use of drones in agriculture will not take off (Simelli & Tsagaris, 2015; Stafford, 2000).

2.4. Economics of Precision Agriculture

All of the new technologies being developed in the current environment such as VRT, UAS, and other applications to precision agriculture could be helpful for growers to make management decisions, but these technologies need to provide value to the grower in an economic sense. Stafford (2000) suggests three barriers to precision agriculture adoption in the 21st Century: excessive amounts of data, lack of "formalized methods for determining management zones and application needs," and that precision agriculture is costly and labor intensive (p. 269). The first two barriers have been discussed in the previous sections while the last barrier will be discussed here.

Ideally, within precision agriculture, growers would want to know real time information on how each and every plant is doing within the field. While some of these technologies are beginning to provide this data, due to the current large costs, knowing what is going on in each plant is not feasible in production agriculture. Because of this, most of the plants and field will not be sampled and overall plant yield will remain inconstant (Buttafuoco, Castrignanò, Cucci, Lacolla, & Lucà, 2017). This does not mean that growers should give up hope on making precision agriculture a viable option in their operations. Managing location variability in fields will offer growers the opportunity to save by efficiently applying nutrients in the right place when the plant is in need of those nutrients (Turner et al., 2016). This practice has been implemented and proven especially in regards to nitrogen fertilizer applications (Jones et al., 2015).

Not all growers have adopted precision agriculture in their operations, and while this practice is the future of agriculture, there might actually be some benefits to growers being late adopters. Precision agriculture technologies are, for the most part, very costly to implement and some processes and techniques are yet to be proven. By being later adopters in precision agriculture, some growers could see substantial cost savings as technology prices continue to decrease (Schimmelpfennig & Ebel, 2016). Additionally, allowing others to perfect how the technologies are used and develop best practices can provide valuable information about how best to implement the technology in their operations; this can also add cost savings (Schimmelpfennig & Ebel, 2016). Precision agriculture non-adopters might also be looking at other costs, like opportunity costs for their time. Many growers who have not adopted these technologies might not be technologically savvy like the people who have adopted (Larson et al., 2005). This leads to increased opportunity costs because the less technologically savvy producer would also have to learn other technologies just to make some precision agriculture work in their operation when they feel like they should be spending more time in the tractor “actually” farming (McSweeney, 2016).

With regard to specific technologies, most precision agriculture technologies will provide growers with added benefits. Specifically, drones with the proper remote sensing technologies attached seem to be a very good method of collecting plant health data, even though parts of the operations are costly and time consuming (Gago et al., 2015). Using the data collected and analyzed from drones can help growers make management decisions, but a drone on its own might not provide the best overall value for the grower. Information collected from the drone will only tell the grower where issues are, but cannot correct the issue. Because of this fact, adopting just one technology might provide value in one sense, but may not be economically feasible unless it is used in combination with other precision agriculture technologies such as VRT when additional cost savings and increased revenues can be realized (Schimmelpfennig & Ebel, 2016). Bullock, Ruffo, Bullock, and Bollero (2009) theorized that precision agriculture technologies used in combination with each other can create greater value to the grower than the technologies utilized on their own. Combining these technologies can help determine which areas of the field are being the most productive and profitable, and which are lower producing areas with less profit (Searcy, 1997).

Overall, "the profitability of precision [agriculture] is as variable as field conditions" (Searcy, 1997, p. 4). Fields that have little variability have a lesser chance than those field with more variability for making precision agriculture something a producer should adopt (Searcy, 1997). When looking at yield maps for a field, there are not very many fields that are uniform or where little opportunity to define different management zones exists. With the information collected from precision agriculture operations, a field's variability can be determined and management decisions can be made to ensure that the largest profit is created for the producer (Searcy, 1997). Ultimately, the decision of a grower to adopt precision agriculture technology is based on economics. As long as the technology provides a profit and there are no other existing technologies that provide a greater profit, the producer would be wise to adopt the technology.

3. EMPIRICAL MODEL

3.1. Producer's Decision to Adopt Technology

Producers face many decisions when it comes to determining which technologies to use in their operations and which technologies to not invest in (Biermacher, Epplin, Brorsen, Solie, & Raun, 2009). Each one of these technologies, whether remote sensing imagery, VRT applications of fertilizer and seed, various pesticide treatments, and even getting a larger piece of equipment look at similar rationale when determining whether to adopt or not adopt a particular technology. The risk-neutral producer would be focused on maximizing profit, so they would choose to adopt a technology if it provides the grower with a profit (Biermacher et al., 2009). Thus, we could denote the decision to adopt as:

$$Producer\ Decision = \begin{cases} adopt, & if\ E(max\,E(\pi_{new})) - E(max\,E(\pi_{old})) > \tau \\ not\ adopt, & otherwise \end{cases} \qquad \text{(Eq. 3.1)}$$

where $\tau \geq 0$ is the cost of change of incorporating the new technologies and $E(\pi_k)$ is the expected profit (dollars per acre) from adopting k technologies (k = { *new, old* }) (Biermacher et al., 2009, p. 215). Changes that result in a difference to the expected profit include the tradeoff between (1) the cost of information or cost of sensing, (2) cost of the VRT application, (3) changes in yield which impact revenues, and (4) change in the cost of directly costed inputs such as fertilizer where the rate can be specifically identified in each portion of the field (Biermacher et al., 2009; Lowenberg-DoBoer, 1999; Stefanini, 2015). Conditions unique to each field and site-specific region may also exist relating to soil types and weather, which further complicates the decision of how many additional inputs should be applied to each area (Bullock and Bullock, 1994; Lowenberg-DoBoer, 1999).

One of biggest components to adopting precision agriculture technologies is the additional cost of information associated with gathering and analyzing the data to make the decisions about the amounts of inputs to place in each specific area (Bullock, Lowenberg-Deboer, & Swinton, 2002). Analyzing the data requires specific knowledge of agronomics, how the technology works and gathers the data, and how agronomics and the results of the data interact with each other. Many producers do not have the resources relating to technology to collect the data especially relating to time or personnel or the resources to process the data into a useful form at which point decisions can be made. In many cases, the producer does not have the ability or knowledge base to make the decisions on his or her own based on the data which is collected and analyzed.

3.2. Estimated Profit from Technology Adoption

The decision to invest in a new technology should largely be driven by the estimated profit that will come from adopting the new technology. In general, the producer is looking at a decision on profit as follows:

$$E(\pi_k) = Y_k * P - NR_k * NP_k - AT_k - OCP \qquad \text{(Eq. 3.2)}$$

where Y_k is the yield per acre with technology k; P is the price received in dollars per bushel and is not influenced by the producer's decision to adopt the technology; NR_k is the rate of fertilizer applied with technology k; NP_k is the cost of fertilizer in dollars per pound of actual fertilizer for technology k; AT_k is the cost of adopting a new technology including remote sensing costs, additional application costs, and costs related to the processing, analyzing, and making a recommendation; and OCP are the other costs of production which are fixed across technologies k which include tillage, typical before season fertilizing costs, seeding, spraying, harvesting, labor, and management. The inputs of NR_{new} and NP_{new} are typically variable across the field and AT_{new} is typically a fixed cost per acre.

One key assumption made in this study is that growers in North Dakota do not normally make sidedress applications of nitrogen in their fields. This particular technology that is being studied allows the grower to make a decision whether or not to make an additional nitrogen fertilizer application during the season. With this assumption in mind, we can look at the two profit equations for the new technology and the old technology more in depth.

Applying equation 3.2 to the old technology, we get the following:

$$E(\pi_{old}) = Y_{old} * P - OCP \qquad \text{(Eq. 3.3)}$$

because NR_k equals zero since no additional fertilizer will be applied and AT_k is zero also because the grower would not adopt the technology.

Using the same method as in equation 3.3 above, we apply the new technology to equation 3.2; the following results:

$$E(\pi_{new}) = Y_{new} * P - NR_{new} * NP_{new} - AT_{new} - OCP \qquad \text{(Eq. 3.4)}$$

Taking equations 3.3 and 3.4 and placing them in equation 3.1, we would get the following:

$$Y_{new} * P - NR_{new} * NP_{new} - AT_{new} - OCP \geq Y_{old} * P - OCP \qquad \text{(Eq. 3.5)}$$

using the assumption that the grower would adopt the new technology if the expected profit of the new technology is greater than that of the old technology. In this case, we will also make the assumption that the grower would invest in the new technology if it did not cost the grower anything to adopt the technology. This assumption can be made because the grower will likely get intangible benefits from adopting the technology like being able to predict yield and better market the crop, having a better piece of mind about how the crop is doing, the ability to collect and retain the data for future use, or because this technology will allow the grower to adopt another technology which will have a greater return than without both technologies creating synergies. There are also other cases where the grower might decide to adopt the technology even when the return is negative. These cases might include spreading out the labor during the growing season rather than doing it all in the fall or spring, environmental effects, or the ability to receive lower input prices during the season, as examples. The economics of these decisions will not be discussed in this paper, but would be worth researching in the future.

Taking equation 3.5 and simplifying it so the results can be easily analyzed, the following equation results:

$$P * (Y_{new} - Y_{old}) - NR_{new} * NP_{new} - AT_{new} \geq 0 \qquad \text{(Eq. 3.6)}$$

This equation shows the decision to adopt is essentially the change in the yield from the new technology to the old technology minus the costs of adopting the new technology which includes the additional variable inputs of NR_{new} and NP_{new} and the fixed inputs of AT_{new}.

3.3. Yield Estimates from Technology Adoption

As noted above in equation 3.6, yield is a big part of the expected profit equation and is the multiplier used with the price received by the producer to determine the revenue from production operations. Yield can be shown with the following equation:

$$Y_{k,l} = f(CI_l, N_l, O_l, S_l) \qquad \text{(Eq. 3.7)}$$

where $Y_{k,l}$ is the yield in bushels per acre for technology *k* and location *l* (Stefanini, 2015). Location *l* is a management zone within the field (small acreage), which can be identified geographically and where each input difference can be tracked. *CI* denotes crop inputs used in the production of the crop. Some inputs may be unknown like chemicals applied for herbicide, fungicide, and insecticide applications, seed treatments, seed traits and technologies, and tillage methods as examples, but also could include known variables, in some cases, like variable population, multiple hybrids, and additional inputs such as lime or fertilizers relating to in furrow starter. *N* is the fertilizer rate based on the need from the technology in use and being adopted. *S* is information on the field soil properties including soil types and slopes (Stefanini, 2015). The last variable in the equation is *O*, which includes a number of different factors the producer does not have control over like the conditions of the growing season such as moisture, temperature, wind, hail, insect pressure, and weed pressure, for example. *O* also includes other factors that cannot be identified when estimating yield similar to the error value in a regression.

These four factors used to estimate yield are variables that may be able to be controlled by the producer at varying levels. For instance, the grower who knows his or her land might be able to maximize the yield by selecting the proper crop inputs and in-season fertilizer applications for the field based on agronomic knowledge. Some of these decisions might include putting a seed treatment on the seed because there has been a history of seed-borne disease in the field or applying a fungicide when disease pressure is high. On the other hand, while the grower might think it would be best to switch to a different management practice such as cover cropping or strip tilling, the grower might not be able to make these changes relatively easily. Comparatively, weather and other are factors that cannot be controlled by the grower and subject the grower to chance and probabilities.

In the case of this study, it is proposed that we add one additional variable to the yield function. This value would be the NDVI reading for the field at various times during the growing season. Even though this variable does not specifically impact the yield, it is a good estimator of yield and will be included in the model when predicting yield (Badu, 2016; Mkhabela et al., 2011; Tucker et al., 1979). Thus, the new yield equation updated from equation 3.7 is as follows:

$$Y_{k,l} = f(CI_l, N_l, NDVI_{l,t}, O_l, S_l) \qquad \text{(Eq. 3.8)}$$

where *NDVI* is checked at time *t* throughout the growing season in locations *l*. In this equation, all variables are exogenous variables with the exception of the *NDVI* variable, which would be an endogenous variable because the factors of *CI*, *N*, *O*, and *S* all will cause the *NDVI* to vary across location *l*.

3.4. Costs of Technology Adoption

The other components of the profit function are the added costs of technology adoption. These costs include the variable costs of NR_{new} and NP_{new} and the fixed inputs of AT_{new}. NP_{new} is the price of the new fertilizer plan the grower is adopting with the new technology. Most commonly, this is in the form of 28% UAN liquid fertilizer, which can be applied using VRT technology in a sidedress application. Typically, sidedress applications are applied using technologies that can apply large quantities of product in one area rather than dispersing the product uniformly across the area like with a sprayer. Franzen (2013) recommends using a coulter type application for row crops, but also finds using a stream type application as effective in row crops and the main option available for growers with solid seeded and small grain type crops. The price for the in-season application of fertilizer will typically be higher than that of fall or spring applied fertilizer due to the nature of the fertilizer type (UAN) being used.

The rate of fertilizer (NR_{new}) applied to the fields in this study was done using the Nitrogen Use Efficiency method developed by researchers at Oklahoma State University (Arnall, Tubaña, Holtz, Girma, & Raun, 2009; Raun et al., 2002; Raun, Solie, & Stone, 2011). In this method, the grower uses nitrogen fertilizer test strips within the field. This practice is based on predicted yield potential in the crop and is determined by placing a nitrogen rich strip in the field where nitrogen is not limited or a series of strips in the field with varying rates of nitrogen to determine the optimal rate of nitrogen fertilizer that should be placed in the field (Arnall et al., 2009). Determining the optimal rates of fertilizer applied to each area make this item vary from place to place in the field and may even change as the growing season progresses through the year. This particular study will focus on the profitability of applying the additional in-season fertilizer and will not focus on determining the optimal rate of fertilizer to be applied to specific areas in the field and are done on an ex-post basis.

The other costs associated with adopting technology are the fixed costs of adopting the technology and denoted as AT_{new}. These costs are flat costs that are incurred when adopting the technology. For instance, some of these costs may be the fees related to remote sensing from a drone using NDVI, the charges from the consultant to make the agronomic recommendations from the NDVI data and creating a VRT prescription, and the costs to apply the fertilizer in the designated locations that do not change like custom application charges.

3.5. Summary

The model being employed in the study is one focusing on the expected profit of adopting a new technology. Specific focus in the model will be on estimated yields, the costs of applying additional fertilizer, and the added costs of adding the technology.

4. DATA AND RESULTS

This chapter will cover the collection of the data used in this study. A general overview of how all data were collected is presented followed by specific data for each field used in the study. Following the specific data, are unique results from each field. A summary of results will follow the field level data.

4.1. Collection of Data

The data used in this study was collected during the 2015, 2016, and 2017 growing seasons from four growers in various locations throughout the state of North Dakota with one of three crops: corn, hard red spring wheat, or soybean. Growers were selected who were interested in adopting the remote sensing technology of collecting NDVI data using drones. The decision was then made using the NDVI data to determine whether or not an application of in-season nitrogen was needed to help reach the maximum yield potential. If an additional nitrogen application was applied, as-applied data were collected from this operation. During harvest, yield data were collected and was used in determining the model. Other data such as applications of lime or phosphate, soil survey data, pre-season nitrogen, variable rate seeding, and multi-hybrid seeding maps were used to estimate yield.

4.1.1. NDVI Data

NDVI data were collected from each field once each during the month of June, July, and August except for in the case of spring wheat when only data were collected in June and July due to the early harvest of this crop. A consultant flying various drones collected the data with a Sentera High-Precision NDVI sensor (Sentera 2017a, Sentera 2017b). After the data were collected, it was then processed from the RGB and NIR imagery into NDVI data by the software

Pix4D, which was used to take the photos and stitch them together into a georeferenced mosaic in TIF format or raster.

Once the data were processed into a TIF orthomosaic, it was then put into the software ArcMap where it was further processed (ESRI, 2015). Within the ArcMap software, the data were transformed into point data using the Raster to Point process within the software. This process takes the raster or orthomosaic and places it in a shapefile format. Within the shapefile format, the data can then be analyzed and placed with geographical coordinates. At this stage, the points created in the shapefile are located one half meter to one meter in distance from each other depending upon the resolution of the raster data and the flight level of the UAV.

The NDVI data collected at this stage encompassed the entire field level and also some additional images on the outside of the field including the road ditch, road, and some of the neighboring fields. Removing the outlying data that was not field level data, was done using the Clip procedure in ArcMap. The shape of the field used to Clip the NDVI data was the yield data layer, which in turn created the field boundary, discussed later in this chapter. An example of the raw and clipped NDVI data is located in Figure 4.1.

Following the previous analytics, a Fishnet procedure was run in ArcMap to create grids over the fields. Each created grid was two meters by two meters square, totaling just fewer than one thousandth of an acre. This meant that a field of about 160 acres would have around 160,000 two-square-meter grids. Each one of these grids was then used as a reference for the other data collected in the field. An example of the four-square-meter fishnet grid is located in Figure 4.2.

After the grid creation, a Spatial Join process was ran to merge the shapefile data into each georeferenced grid. During Spatial Join process, data for each grid collected included the mean, minimum, maximum, standard deviation, and count of each point collected from the NDVI layers. This process was repeated for each NDVI layer collected within the field.

4.1.2. Yield Data

Yield data for each field was collected from each grower using their own pieces of equipment and monitors. Information on whether or not the combines were properly calibrated at the time of data collection was not available. Raw geo-referenced yield data were taken from each combine in comma separated value files and was imported in the Yield Editor software (USDA ARS, 2016). Yield data were then cleaned based on the automatic cleaning process described in Suddoth, Drummond, and Myers (2012). After running the automated cleaning process in the Yield Editor software, data were then imported into the SMS Advanced software (Ag Leader, 2017). From this point, yield data were used in two different manners: 1) to create the boundary polygon, and 2) for the data analysis, both of which will be described below.

In the SMS Advanced software, a field boundary was created based on the data that were collected during harvest time using the Copy from Layer process within the software. This particular process takes the data from the base layer, in this case the yield map, and identifies a pattern in the data to determine the boundary. The software uses the data where the yield is greater than zero and places a polygon around these locations. After the software creates the boundary polygon, individual places can be adjusted by the user to fix errors in the process where the polygon was created incorrectly. It should be noted that at this stage, if there were any locations in the field that had zero yield such as drowned out spots, weedy spots, etc., these locations in the field were not included in the boundary. The researcher decided to exclude these points because, most likely, there would have been NDVI readings in these locations but no yield. At a later stage in the data processing and regressions, the spots with NDVI readings and no yield would have caused additional error and a decrease in the accuracy of the model. Thus, some locations in the middle of the field may have been excluded and can be easily identified on the maps because they appear as large white spots. The boundary polygon created in SMS Advanced was then exported as a shape file and imported into the ArcMap software as described above. This boundary polygon was then used to determine the field boundaries for all additional layers in the analysis and was used to Clip the data, as described in the NDVI section of this chapter.

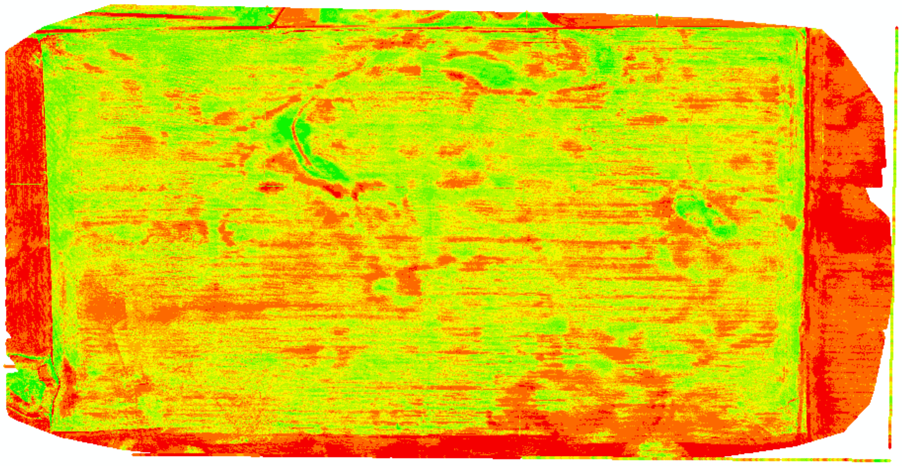
The clean yield data from the Yield Editor software were also imported into ArcMap to be analyzed with the NDVI and additional field level data. Since the data from the field monitors in the combines were point data in the comma separated value format, the exact shape of the yield box created from the combine during harvest was not known. Due to this factor, the yield data were used to create Thiessen polygons, which extrapolate the shape of the yield boxes based on the location of the other data points. In most cases, these Thiessen polygons emulate what the actual yield polygon shape from the combine would have generated. Additionally, by creating the Thiessen polygons from the yield data, spaces that may have been missed by the combine would also be extrapolated and no spots with the field boundary would have a value of zero for yield per acre. The yield polygons created by the Thiessen polygon process in ArcMap were then spatially joined to the NDVI fishnet maps using the Spatial Join procedure as described in the previous section. An example of yield data after running the Thiessen polygon process is located in Figure 4.2.

The Thiessen polygon process also helps with another issue from the raw yield data. The cleaned yield data from the combine is point data as mentioned above. Due to the size of the fishnet grids created (i.e., four square meters), the yield data would have only been located in approximately one of three or four fishnet grids. Having reduced the data's sample size by this manner might have significantly altered the result of the study due to such limited use of the NDVI data.

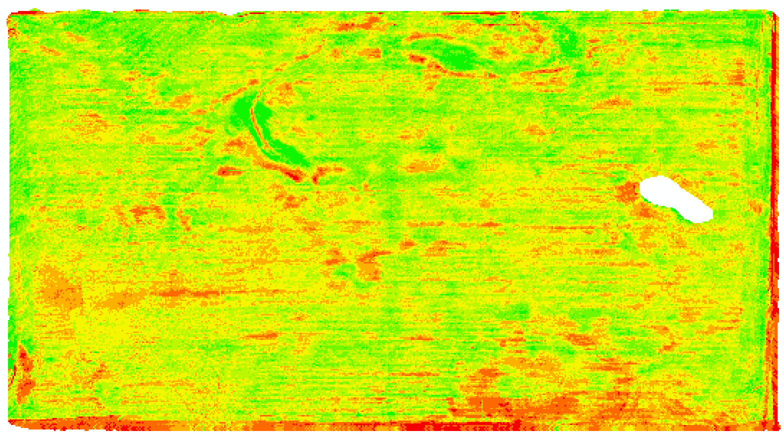
The yield Thiessen polygons were also used in a manner similar to creating a fishnet over the field. In this case, the shape of the yield Thiessen polygons was used as the base to create the grids in the field. After these Thiessen polygons were created, the NDVI data were spatially joined together. This data and the other field data were used to run an analysis similar to what will be described a little later in this chapter. No significant differences in the regression estimates resulted, so the field analysis was continued using the four-meter fishnet grids.

4.1.3. Soil Data

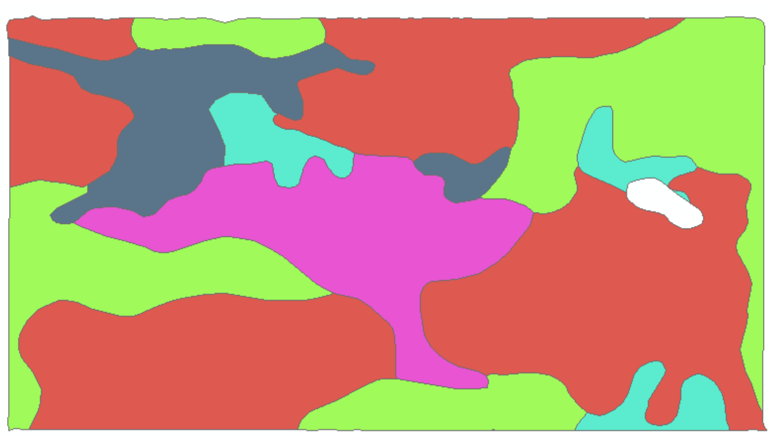
Using the boundary created from the yield data in SMS Advanced, soil data were gathered from the United States Department of Agriculture (USDA) Natural Resources Conservation Service (NRCS) Soil Survey (USDA NRCS, 2017). SMS Advanced has an option within the software that will download the information from the NRCS Soil Survey based on the field boundary. This option was used to download the information on the soil profiles for each field. All data from the soil survey was retrieved, but the only data used in the analysis were the soil symbol and soil descriptors. Within the soil symbol, information based on the soil type and slope information in each area is identified. From SMS Advanced, these soil data were exported as a shape file and then imported into ArcMap. An example of soil data is located in Figure 4.1.



Example of Raw NDVI File – Red Shows Lower Vegetation, Green Shows Higher Vegetation



Example of Clipped NDVI – Red Shows Lower Vegetation, Green Shows Higher Vegetation



Example of Soil Survey Data – Field Clipped by Field Boundary

Figure 4.1. Examples of Field Level Data

The data imported into ArcMap were then joined to the four-square-meter fishnet grids so that each one of the fishnet grids had the soil symbol identified. During this process, dummy variables were created for each different soil symbol. The proper dummy variable was selected based on the mode selection method, which caused the soil symbol with the most area in each grid to be selected. Due to the different location of each field, the soil symbols are mostly different between the fields used in this study. Soil symbol was used as one factor to determine the variability of yield within each field.

4.1.4. In-Season Fertilizer Application Data

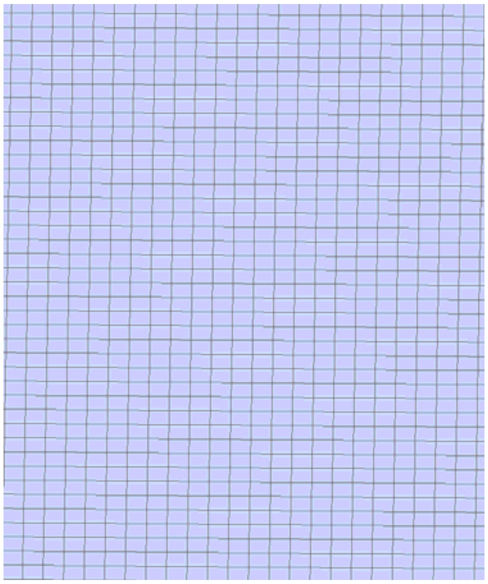
The fields in the study had nitrogen applied to them while the plants in the field were actively growing. The decision to make this application was determined based on the recommendation of the consultant using the imagery collected from the drone and sensor package. In some cases, the researcher received as-applied field data and in other cases, only the prescription created by the agronomic consultant was received. Depending upon the data received, different processes were used to handle the data.

When as-applied data was received for the field, the data were in a format similar to the yield data from the combines. Making sure these data were not in a point format was critical to ensure the data were correctly distributed across the fishnet grids. In one of the fields, the as-applied data were collected on a sprayer that was 120 feet wide. With a machine of this size, there would only be a data point (from point format data) one every thirteen or fourteen fishnet grids. The as-applied data were imported into ArcMap and the Thiessen polygon process was ran. These data were then combined with the yield, NDVI, and soil data using the Spatial Join process. An example of sidedress as-applied data is located in Figure 4.2.

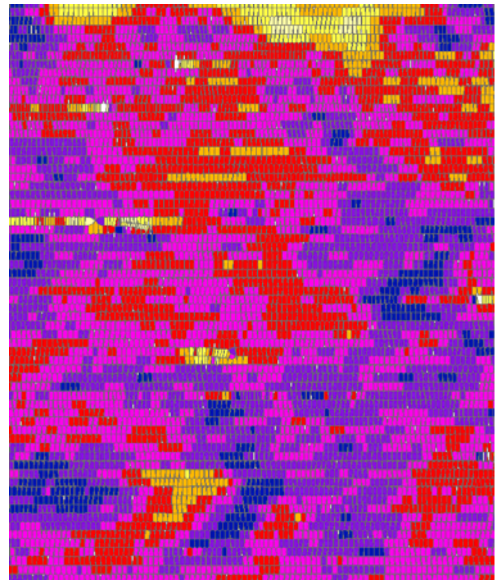
The data received from the agronomic consultant was not always the as-applied data, but sometimes the data were the prescription for the in-season fertilizer application. In this case, the data came to the researcher in a TIF format, which were raster data. The raster files were imported into ArcMap where the file was processed using the Raster to Point process. The new point file had data that were approximately 1.33 meters away from each other. When the spatial join process was ran to combine the data layers together, the result merged from one to four points per fishnet grid.

4.1.5. Other Data

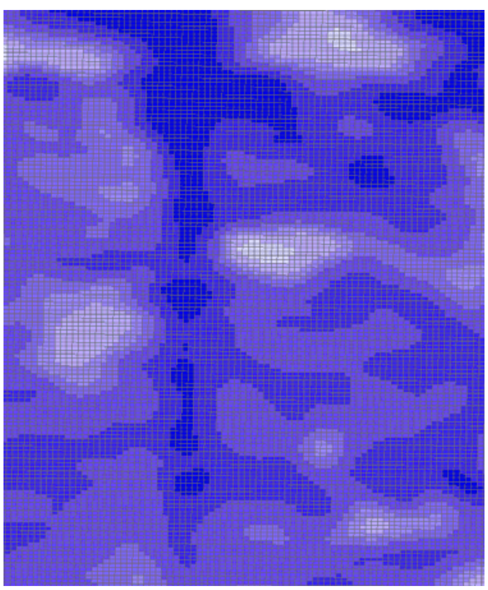
Each field used in the study could also have a number of other data files. In most cases, these files came to the researcher as TIF files. These files were imported into ArcMap where they were converted from raster data to point data similar to the process done with the NDVI and prescription in-season fertilizer application data. Some of these files which might be present in the data include: as-applied or prescription data for lime applications, pre-season nitrogen and sulfur fertilizer applications, phosphorus applications, variable seeding population maps, multi-hybrid seeding maps, and liquid starter fertilizer. These data were typically located in management zones created by the consultant for use by the grower. If other types of files were received, the data would have been processed similar to that of the yield data using the Thiessen polygon process. An example of a multi-hybrid variable planting map is located in Figure 4.2.



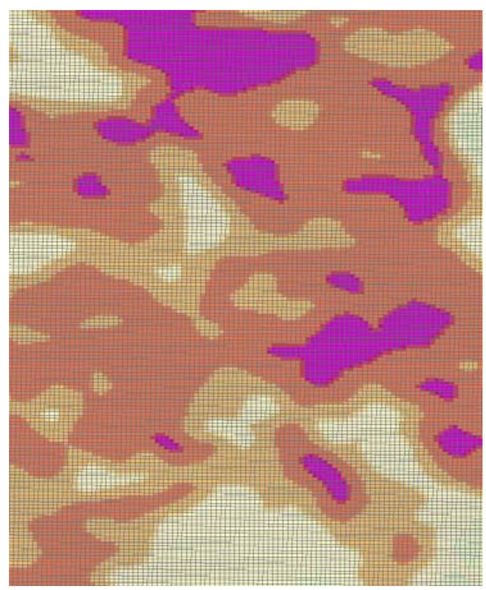
Example of Two Square Meter Fishnet Grids Used for Analysis



Example of Yield Data after Applying Thiessen Polygon Process – Yellow (Lower Yield), Red (Medium Yield), Blue (Higher Yield)



Example of Sidedress Application Data – Darker Colors Indicate Higher Rates



Example of Multi-Hybrid Variable Planting Map – Purple Shows High Rates of Hybrid A, Orange Shows Low Rates of Hybrid A, Yellow Shows Areas with Both Hybrids, White Shows Low Rates of Hybrid B

Figure 4.2. Close-Up Examples of Field Level Data

4.2. Analysis of Field Data

The data combined together in ArcMap were then ready for statistical analysis. This was done by exporting the data table from ArcMap in a comma separated value file that could easily be imported into the statistical software. The statistical software used to run the regression models was SAS (SAS Institute, 2013). The data were then filtered to remove erroneous data from the dataset to make sure these values were not included in the analysis. Some examples of the data removed are: places where NDVI readings were not available, locations where yield data did not accurately get merged into the data set, and areas where other data were missing for some reason. In most cases, the data removed in this step was less than 0.5% of the data points.

The filtered data were then ready for analysis in the software. Within SAS, a standard regression was run using the PROC REG procedure. Yield was set as the dependent variable and the other factors were set as independent variables in the model. In the cases where dummy variables were present (i.e. soil data and multiple hybrids) the dummy variable with the lowest number of observations was used as the reference to determine significance with the other factors. Additionally, a heteroscedasticity test was ran using White's method and the error terms were determined to be correlated with the other variables, so all of the error terms in the model are listed using White's correction for heteroscedasticity.

The data were then analyzed in a manner to determine different management zones within the field. In the cases where there were variable seeding rates, the seeding rates were analyzed in SAS using a horizontal bar chart to determine the distribution of the plant population throughout the field. These areas were used as management zones to identify the different productivity levels in the field. The management zones located in the field were created by the agronomic consultant through a combination of past yield history, soil test results, and imagery.

Each different management zone was analyzed to determine how the in-season fertilizer application affected yield and also profitability.

Analyzing profitability was done using the regression values from the model for each field. Price and cost information was collected from the North Dakota State University Extension Service Crop Budgets for the specific information based on the field such as crop, year, and location. Predicated yield estimates were used in the model in conjunction with the crop budget prices to determine revenues in each management zone. Cost estimates from the crop budgets were used, but some of the data from the budgets were adjusted based on the information used in the management zone. One instance of when budget data were adjusted is where variable rate planting maps were available; the estimated cost of seed for each management zone was calculated. Furthermore, in areas where in-season fertilizer rates were variable, the variable cost of fertilizer and cost of in-season fertilizer applications were also used to calculate the total cost in each management zone. In-season fertilizer applications costs were collected from the U.S. Department of Agriculture's North Dakota Agricultural Statistics Service and the North Dakota State University Extension Service in 2016. The mean value of $9.75 per acre was used even though data ranged from five to twenty dollars per acre because it was thought to be the closest representation of actual costs a producer would incur per acre (Haugen, 2017). From this point, costs were subtracted from revenues and estimated profit was calculated. Data were then summarized to determine the differences in profitability between the management zones within the field.

4.3. Individual Field Level Data

The next section includes the summary of the data for the individual fields used in this study. Each field has unique values and results that will be discussed at the field level. After all field data has been reported, overall results will be listed in the next section.

4.3.1. Chuck North

The Chuck North field is a cornfield located in the Southeast NDSU Crop Budget region from the 2016 growing season. NDVI was collected on June 23rd, July 22nd, and September 1st. The field was planted using variable rate technology and the seeding rates were varied throughout the field with two different corn hybrids. Corn hybrid A was used in the higher producing areas while corn hybrid B was used in lower producing areas of the field. Corn hybrid A was located in 84% of the field, while corn hybrid B was located in the balance of the field. This particular field also had MAP or 11-52-0 fertilizer applied to it in the fall prior to planting and two applications of 28% UAN fertilizer were made on this field and were the primary nitrogen source for this field. Soil types in the field were Barnes-Cresband loam with three to six percent slope, Barnes-Svea loam from zero to three and three to six percent slope, Tonka silt loam with zero to one percent slope, and Parnell silty clay loam with zero to one percent slope.

The data from each of the grids were regressed to determine yield. The values from the NDVI collected in June, July, and September along with soil types, sidedress rate, MAP rate, corn hybrid, and seeding rate were used as independent variables and 200,120 grids were used in the regression for an adjusted R^2 of .2724. The regression values are listed in Table 4.1.

The field was divided into seven management zones based on the corn hybrid and seeding rate. Corn hybrid A had three zones with high population where seeding rate was over 34,000 seeds per acre, low population where seeding rates were less than 33,000 seeds per acre, and medium population between the high and low populations. Corn hybrid B had two zones where high population was above 26,000 seeds per acre and low population was below the same value. There were also two zones where both hybrids were located and these locations were divided based on the prominent hybrid available in that grid. The population zones were determined by looking at the data and identifying natural breaks within the data, which would could be easily divided. Overall, corn hybrid A-high population accounted for 17% of the field, corn hybrid A-medium population was 31% of the field, corn hybrid A-low population was 33% of the field, corn hybrid B-high population was 9% of the field and the remaining zones were 3-4% of the field each (may not add up to 100% based on rounding).

Table 4.1. Summary of Regression Values for Chuck North Field

Variable	Beta (White's Error Value)
Intercept	-108.1188 *** (5.56)
June NDVI Mean Beta	94.7746 *** (4.71)
July NDVI Mean Beta	-159.1167 *** (16.45)
July NDVI Min Beta	149.3975 *** (7.78)
July NDVI Max Beta	100.7207 *** (10.18)
Sept NDVI Mean Beta	106.4866 *** (32.54)
Sept NDVI Min Beta	61.0107 *** (19.58)
Sept NDVI Max Beta	-19.7504 (12.20)
G122B Dummy	-4.8966 *** (0.31)
G143A Dummy	-4.9147 *** (0.30)
G143B Dummy	-6.4571 *** (0.31)
G2A Dummy	-0.2387 (0.34)
28% UAN Rate (GPA)	0.7963 *** (0.02)
MAP Rate (lbs/acre)	0.2719 *** (0.00)
Hybrid A Dummy	-11.6302 *** (0.44)
Seeding Rate (Seeds/acre)	0.0016 *** (0.00)

Four calculations were completed for each field based on the regression values to estimate the profitability of each treatment application. These calculations include applying the maximum rate of nitrogen to each grid, the mean rate of nitrogen to each grid, the minimum rate of nitrogen to each grid, and no nitrogen applied to each grid. The mean rate of nitrogen applied is the farmer's current field practice. The maximum rate is used to determine how well the farmer practice is working. Minimum rate and no nitrogen applied are used to determine how profitable it would be if the producer did not use the technology to determine sidedress rates. This process is repeated in each field. Field level costs and revenues were calculated using the 2016 Crop Budget from the NDSU Extension Service (Swenson & Haugen, 2015a). Results for profitability are listed in Table 4.2.

Table 4.2. Profitability for Chuck North Field by Management Zone and Nitrogen Rate

Management Zone	**Profit – Maximum Nitrogen Rate**		**Profit – Farmer Practice Nitrogen Rate**		**Profit – Minimum Nitrogen Rate**		**Profit – No Nitrogen Applied**	
	Mean	Std	Mean	Std	Mean	Std	Mean	Std
Both Hybrids – Mostly A	159.63	24.78	141.98	25.79	133.06	24.78	77.99	24.78
Both Hybrids – Mostly B	166.74	26.64	159.83	28	145.1	26.64	103.45	26.64
Hybrid A – High Pop	172.95	32.08	170.5	32.04	163.22	32.08	70.03	32.08
Hybrid A – Medium Pop	180.5	24.31	174.06	23.81	167.2	24.31	83.42	24.31
Hybrid A – Low Pop	185.36	24.21	171.78	25.53	154.51	24.21	93.79	24.21
Hybrid B – High Pop	138.84	28.93	124.9	32.01	112.28	28.93	79.48	28.93
Hybrid B – Low Pop	52.06	44.54	36.84	46.74	31.91	44.54	7.54	44.54
All	**171.04**	38.27	**161.46**	39.96	**150.31**	39.1	**81.84**	32.14

This particular field shows great returns when using 28% UAN in a sidedress application. Expected profit from each grid is expected to be double of what it would be without using the sidedress application from NDVI data. Additionally, if the grower would have applied the maximum nitrogen rate in each zone, additional profitability would have only increased around $10 per acre which shows that a near optimum nitrogen rate was applied.

4.3.2. Faught

The Faught field is a cornfield located in Southern Valley NDSU Crop Budget region from the 2017 growing season. NDVI data were collected on June 30th, July 31st, and August 30th. The field was planted using variable rate technology and the seeding rates were varied in the field based on previous years' yield data and satellite imagery. This field also had some starter fertilizer applied at the time of seeding that was highly correlated with population rate (r = .948). Soil types in this field are Fordville loam, Gardena loam, and Antler-Wyard loams with slopes from zero to two percent each.

The data from each of the grids were regressed to determine yield. The values from the NDVI collected in June, July, and August along with soil types, sidedress rate, starter fertilizer rate, and seeding rate were used as independent variables and 148,917 grids were used in the regression for an adjusted R^2 of .3376. The regression values are listed in Table 4.3.

This field was divided into three management zones based on the corn seeding population rates. The high population zone was where seeding rate was greater than or equal to 32,000 seeds per acre, which accounted for 43% of the field. The low population zone was where the seeding rate was below 29,500 seeds per acre and accounted for 28% of the field. The medium population zone was located between the high and low population zone and accounted for 29% of the field. The same four calculations were conducted as in the Chuck North field to determine profitability in each management zone and the results are summarized in Table 4.4. Field level costs and revenues were calculated using the 2017 Crop Budget from the NDSU Extension Service (Swenson & Haugen, 2017).

Table 4.3. Summary of Regression Values for Faught Field

Variable	Beta (White's Error Value)
Intercept	7.4441 *** (2.69)
June NDVI Mean Beta	-75.1116 *** (10.72)
June NDVI Min Beta	52.7739 *** (5.25)
June NDVI Max Beta	45.0306 *** (6.69)
July NDVI Mean Beta	-96.8109 *** (13.77)
July NDVI Min Beta	105.0284 *** (8.12)
July NDVI Max Beta	-69.1672 *** (6.92)
August NDVI Mean Beta	196.1428 *** (2.28)
I500A Dummy	16.3373 *** (0.33)
I504A Dummy	1.2346 *** (0.33)
Seeding Rate (Seeds/acre)	0.0011 *** (0.00)
Starter Fert Rate (GPA)	-1.2826 *** (0.20
28% UAN Rate (GPA)	3.9719 *** (0.13)

Table 4.4. Profitability for Faught Field by Management Zone and Nitrogen Rate

Management Zone	Profit – Maximum Nitrogen Rate		Profit – Farmer Practice Nitrogen Rate		Profit – Minimum Nitrogen Rate		Profit – No Nitrogen Applied	
	Mean	Std	Mean	Std	Mean	Std	Mean	Std
High Pop	12.52	39.90	6.30	42.01	-5.33	39.90	-110.36	39.90
Low Pop	-37.52	47.89	-46.01	48.28	-63.75	47.89	-135.39	47.89
Medium Pop	-13.61	45.87	-30.46	46.53	-35.65	45.87	-132.85	45.87
All	**-9.40**	48.73	**-19.39**	50.59	**-30.86**	50.31	**-124.09**	45.61

This particular field shows negative returns per acre when planted to corn, but large differences between where no nitrogen rate was applied and where nitrogen was applied. The negative returns in this field are a function of the expected corn price per acre and the high overall total costs for production in the 2017 growing season.

4.3.3. Junkyard

The Junkyard field is a cornfield located in Southern Valley NDSU Crop Budget region from the 2017 growing season. NDVI data were collected on June 30th, July 31st, and August 30th. The field was planted using variable rate technology and the seeding rates were varied in the field based on previous years' yield data and satellite imagery. This field also had some starter fertilizer applied at the time of seeding that was highly correlated with population rate (r = .971). Soil types in this field are Aberdeen silt loam, Lankin-Gilby loams, and Gardena loam, Fordville sandy loam with slopes from zero to two percent each and Flom loam with zero to one percent slope.

The data from each of the grids were regressed to determine yield. The values from the NDVI collected in June, July, and August along with soil types, sidedress rate, starter fertilizer rate, and seeding rate were used as independent variables and 134,161 grids were used in the regression for an adjusted R^2 of .5388. The regression values are listed in Table 4.5.

Table 4.5. Summary of Regression Values for Junkyard Field

Variable	Beta (White's Error Value)
Intercept	-44.868 *** (4.31)
June NDVI Mean Beta	-81.174 *** (19.76)
June NDVI Min Beta	20.7586 ** (8.37)
June NDVI Max Beta	-94.656 *** (12.97)
July NDVI Min Beta	54.2607 *** (4.66)
July NDVI Max Beta	-141.77 *** (6.02)
August NDVI Mean Beta	262.605 *** (15.65)
August NDVI Min Beta	49.5319 *** (7.83)
August NDVI Max Beta	-156.75 *** (9.52)
I250A Dummy	6.555 *** (0.34)
I503A Dummy	12.4588 *** (0.24)
I500A Dummy	12.9706 *** (0.22)
I667A Dummy	-2.709 *** (0.37)
Starter Fert Rate (GPA)	-27.941 *** (0.68)
28% UAN Rate (GPA)	25.9951 *** (0.52)
Seeding Rate (Seeds/acre)	0.0071 *** (0.00)

This field was divided into three management zones based on the corn seeding population rates. The high population zone was where seeding rate was greater than or equal to 32,000 seeds per acre, which accounted for 61% of the field. The low population zone was where the seeding rate was below 29,500 seeds per acre and accounted for 21% of the field. The medium population zone was located between the high and low population zone and accounted for 19% of the field. The same four calculations were conducted as in the Chuck North field to determine profitability in each management zone and the results are summarized in Table 4.6. Field level costs and revenues were calculated using the 2017 Crop Budget from the NDSU Extension Service (Swenson & Haugen, 2017).

Table 4.6. Profitability for Junkyard Field by Management Zone and Nitrogen Rate

Management Zone	**Profit – Maximum Nitrogen Rate**		**Profit – Farmer Practice Nitrogen Rate**		**Profit – Minimum Nitrogen Rate**	
	Mean	Std	Mean	Std	Mean	Std
High Pop	103.87	36.47	72.94	26.20	0.49	36.47
Low Pop	43.91	71.83	-85.63	87.71	-292.48	71.83
Medium Pop	131.79	37.25	35.46	43.02	-14.79	37.25
All	**96.55**	54.60	**32.88**	79.17	**-63.49**	126.49

This particular field shows very large differences between the different rates of nitrogen applied to the field. In this case, the no nitrogen application was eliminated from the table because they showed unrealistic negative values of approximately $-800 per acre since total costs are only $490 per acre. The reason for the big variations in the differences of the profit are from the large multiplier of approximately 26 bushels per acre per gallon of 28% UAN applied from the estimated slope value on the sidedress variable. In this case, this seems a little extreme since most corn varieties will give approximately one bushel to 1.5 bushels per pound on nitrogen, as an example. Calculating the squared value of the nitrogen rate to see if there are any quadratic effects present in this case might reduce these issues, but the researcher did not evaluate this instance. Thus, there is something else going on in this field, which would explain yield that was not able to be determined in this regression model.

4.3.4. Kingsley

The Kingsley field is a wheat field located in East Central NDSU Crop Budget region from the 2016 growing season. NDVI data were collected on May 24th and July 15th. This field had two applications of nitrogen fertilizer once on June 29th and again July 7th. Each application was applied to different areas of the field so some areas received an application on both dates, one of the dates, or no application at all. Soil types in this field are: Binford-Coe complex with zero to two percent slope, Divide loam shaley with zero to two percent slope, Embden-Heimdal complex with zero to three percent slope, Embden-Heimdal complex with three to six percent slope, Fram-Tonka complex with zero to three percent slope, Fram-Wyard loams with zero to three percent slope, Hamerly-Tonka complex with zero to three percent slope, Hamerly-Wyard loams with zero to three percent slope, Towner-Heimdal fine sandy loams with zero to three percent slope, Walum sandy loam zero to two percent slope, and Wyndmere fine sandy loam with loamy substratum and zero to two percent slope.

The data from each of the grids were regressed to determine yield. The values from the NDVI collected in May and July along with soil types and sidedress rates were used as independent variables and 160,472 grids were used in the regression for an adjusted R^2 of .1543. The regression values are listed in Table 4.7.

Table 4.7. Summary of Regression Values for Kingsley Field

Variable	Beta (White's Error Value)
Intercept	49.0647 *** (1.73)
May NDVI Mean Beta	64.5185 *** (11.46)
May NDVI Min Beta	55.8628 ** (7.28)
May NDVI Max Beta	-54.464 *** (5.31)
June 28% UAN Rate (lbs/acre)	0.0868 *** (0.00)
July 28% UAN Rate (lbs/acre)	0.0354 *** (0.00)
July NDVI Max Beta	-26.533 *** (2.06)
G101A Dummy	6.6037 *** (0.66)
G210A Dummy	-12.104 *** (0.62)
G211A Dummy	-1.7463 *** (0.67)
G231A Dummy	-7.917 *** (0.59)
G231B Dummy	-10.194 *** (0.60)
G254A Dummy	0.9194 (0.63)
G304A Dummy	-15.537 *** (0.62)
G749A Dummy	2.7668 *** (0.59)

The field was divided into four management zones based on the number of applications of nitrogen fertilizer each grid received. One management zone was where two sidedress applications were made and accounted for 31% of the field total. The second management zone was located where only a sidedress application was applied in June and was 18% of the field. The third management zone had applications only in July and covered 22% of the field. The last management zone had no in-season applications of nitrogen fertilizer and was 29% of the field. Similar calculations to the other fields were calculated to determine profitability. Field level costs and revenues were calculated using the 2016 Crop Budget from the NDSU Extension Service (Swenson & Haugen, 2015a). Data from the minimum profit treatment and the no profit treatment in this case are the same except for the $9.75 application rate which was applied to the minimum profit treatment. As a result, this will be excluded in future analysis, but are listed here for informational purposes. Results for profitability are listed in Table 4.8.

Table 4.8. Profitability for Kingsley Field by Management Zone and Nitrogen Rate

Management Zone	Profit – Maximum Nitrogen Rate		Profit – Farmer Practice Nitrogen Rate		Profit – Minimum Nitrogen Rate		Profit – No Nitrogen Applied	
	Mean	Std	Mean	Std	Mean	Std	Mean	Std
June Sidedress App Only	67.10	36.40	46.61	36.32	17.26	36.40	23.32	36.40
July Sidedress App Only	42.31	39.40	20.62	39.34	13.83	39.40	23.45	39.40
No Sidedress Applications	41.73	26.06	41.73	26.06	41.73	26.06	51.48	26.06
Both Sidedress Applications	138.61	37.27	68.56	37.50	29.36	37.27	38.45	37.27
All	**76.62**	55.12	**46.30**	38.98	**27.34**	36.45	**36.20**	36.65

The results from these management zones are probably some of the most interesting results in the entire study. As shown in Table 4.8, the profitability of applying fertilizer made a large difference between management zones. First, an application in June showed a positive return across the ranges while an application around ten days later would show difference in return similar to that of not making an application. Two different scenarios could explain this difference: 1) the June application was made before a precipitation event which would have meant that most of the fertilizer would have been absorbed by the plants and not volatilized, or 2) the July application was made too late so the plants were past the time when they needed to nitrogen to add yield. This nitrogen would likely not have been wasted, but used by the plant to increase protein, data that was not available to the researcher. In addition, looking at the value of the standard deviation shows greater variability in the July application compared to the no sidedress option, which shows the possibility of greater returns, but also greater risk of loss. Second, it looks as if using a larger amount of nitrogen in season would have given a greater yield to the grower. In this case, the normal field practice profit was $30 per acre less than using the maximum amount of fertilizer, thus additional profit was left on the table.

4.3.5. Raatz

The Raatz field is a cornfield located in the Southeast NDSU Crop Budget region from the 2016 growing season. NDVI was collected on June 23rd and September 1st. The field was planted using variable rate technology and the seeding rates were varied throughout the field with two different corn hybrids. Corn hybrid A was used in the higher producing areas while corn hybrid B was used in lower producing areas of the field. Corn hybrid A was located in 90% of the field while corn hybrid B was located in the balance of the field. This particular field also had lime and MAP or 11-52-0 fertilizer applied to it in the fall prior to planting and one application of 28% UAN fertilizer was made in this field as a sidedress application. Soil types in the field are Hamerly-Wyard loams with zero to three percent slope, Barnes-Svea loams with zero to three and three to six percent slopes, and Parnell silty clay loam with zero to one percent slope.

The data from each of the grids were regressed to determine yield. The values from the NDVI collected in June and September along with soil types, sidedress rate, lime rate, MAP rate, corn hybrid, and seeding rate were used as independent variables and 118,785 grids were used in the regression for an R^2 of .5475. The regression values are listed in Table 4.9.

The field was divided into seven management zones based on the corn hybrid and seeding rate. Corn hybrid A had three zones with high population where seeding rate was over 34,000 seeds per acre, low population where seeding rates were less than 31,000 seeds per acre, and medium population between the high and low populations. Corn hybrid B had two zones where high population was above 25,800 seeds per acre and low population was below the same value. There were also two zones where both hybrids were located and these locations were divided based on the prominent hybrid available in that grid. The population zones were determined by looking at the data and identifying natural breaks within the data that could be easily divided. Overall, corn hybrid A-high population accounted for 22% of the field, corn hybrid A-medium population was 43% of the field, corn hybrid A-low population was 22% of the field, corn hybrid B-high population was 5% of the field and the remaining zones were 2-3% of the field each (may not add up to 100% based on rounding). Field level costs and revenues were calculated using the 2016 Crop Budget from the NDSU Extension Service (Swenson & Haugen, 2015b). Results for profitability is listed in Table 4.10.

Table 4.9. Summary of Regression Values for Raatz Field

Variable	Beta (White's Error Value)
Intercept	-89.339 *** (6.36)
June NDVI Mean Beta	187.587 *** (25.55)
June NDVI Min Beta	74.2596 *** (13.56)
June NDVI Max Beta	-228.99 *** (16.55)
September NDVI Mean Beta	-150.65 *** (44.44)
September NDVI Min Beta	359.668 *** (23.41)
September NDVI Max Beta	-149.38 *** (23.40)
G101A Dummy	30.0193 *** (2.71)
G143A Dummy	47.1494 *** (2.61)
G143B Dummy	50.1401 *** (2.62)
Lime Rate (lbs/acre)	-0.0005 *** (0.00)
MAP Rate (lbs/acre)	0.7179 *** (0.02)
Seeding Rate (Seeds/acre)	0.0019 *** (0.00)
28% UAN Rate (GPA)	1.5384 *** (0.14)
Hybrid A Dummy	16.9898 *** (0.87)

Table 4.10. Profitability for Raatz Field by Management Zone and Nitrogen Rate

Management Zone	Profit – Maximum Nitrogen Rate		Profit – Farmer Practice Nitrogen Rate		Profit – Minimum Nitrogen Rate		Profit – No Nitrogen Applied	
	Mean	Std	Mean	Std	Mean	Std	Mean	Std
Both Hybrids – Mostly A	26.59	45.03	7.12	46.17	0.61	45.03	-58.98	45.03
Both Hybrids – Mostly B	-90.11	53.50	-98.81	54.45	-108.87	53.50	-159.03	53.50
Hybrid A – High Pop	210.74	22.24	205.96	23.61	192.74	22.24	94.96	22.24
Hybrid A – Low Pop	90.33	37.00	79.80	40.19	67.45	37.00	4.48	37.00
Hybrid A – Medium Pop	167.77	29.49	155.31	33.12	136.62	29.49	61.68	29.49
Hybrid B – High Pop	-152.95	55.58	-163.71	58.74	-175.22	55.58	-215.34	55.58
Hybrid B – Low Pop	-300.86	69.02	-315.02	71.91	-320.23	69.02	-352.32	69.02
All	**123.28**	113.07	**112.87**	115.06	**98.02**	112.19	**24.49**	98.53

This particular field shows great returns when using 28% UAN in a sidedress application. Expected profit from each grid is expected to be five times of what it would be without using the sidedress application from NDVI data. Additionally, if the grower would have applied the maximum nitrogen rate in each zone, additional profitability would have only increased around $10 per acre, which shows that a near optimum nitrogen rate was applied.

4.3.6. Tree Grove

The Tree Grove field is a cornfield located in the Southeast NDSU Crop Budget region from the 2016 growing season. NDVI was collected on June 23rd, July 25th, and September 1st. The field was planted using variable rate technology and the seeding rates were varied throughout the field with two different corn hybrids. Corn hybrid A was used in the higher producing areas while corn hybrid B was used in lower producing areas of the field. Corn hybrid

A was located in 91% of the field while corn hybrid B was located in the balance of the field. One application of 28% UAN fertilizer was made in this field. Soil types in the field are Hamerly-Wyard loams with zero to three percent slope, Barnes-Cresbard loams with three to six percent slope, Barnes-Svea loams with zero to three and three to six percent slopes, and Parnell silty clay loam with zero to one percent slope.

The data from each of the grids were regressed to determine yield. The values from the NDVI collected in June, July, and September along with soil types, sidedress rate, corn hybrid, and seeding rate were used as independent variables and 124,058 grids were used in the regression for an R^2 of .2128. The regression values are listed in Table 4.11.

The field was divided into seven management zones based on the corn hybrid and seeding rate. Corn hybrid A had three zones with high population where seeding rate was over 34,500 seeds per acre, low population where seeding rates were less than 31,500 seeds per acre, and medium population between the high and low populations. Corn hybrid B had two zones where high population was above 25,800 seeds per acre and low population was below the same value. There were also two zones where both hybrids were located and these locations were divided based on the prominent hybrid available in that grid. The population zones were determined by looking at the data and identifying natural breaks within the data that could be easily divided. Overall, corn hybrid A-high population accounted for 20% of the field, corn hybrid A-medium population was 40% of the field, corn hybrid A-low population was 20% of the field, and the remaining zones were 2-4% of the field each (may not add up to 100% based on rounding). Field level costs and revenues were calculated using the 2016 Crop Budget from the NDSU Extension Service (Swenson & Haugen, 2015b). Results for profitability is listed in Table 4.12.

Table 4.11. Summary of Regression Values for Tree Grove Field

Variable	Beta (White's Error Value)
Intercept	588.4168 *** (15.68)
June NDVI Mean Beta	-47.4498 *** (9.37)
June NDVI Max Beta	-112.8261 *** (12.40)
July NDVI Mean Beta	-40.6575 * (21.00)
July NDVI Min Beta	200.8445 *** (9.70)
July NDVI Max Beta	-158.1509 *** (14.08)
September NDVI Mean Beta	-625.7014 *** (40.62)
September NDVI Min Beta	497.0015 *** (24.14)
September NDVI Max Beta	131.6246 *** (16.91)
G101A Dummy	4.8646 (3.26)
G143A Dummy	-7.2833 ** (3.19)
G143B Dummy	-8.0281 ** (3.19)
Seeding Rate (Seeds/acre)	-0.0114 *** (0.00)
Hybrid A Dummy	11.9175 *** (0.64)
28% UAN Rate (GPA)	4.3914 *** (0.18)

Table 4.12. Profitability for Tree Grove Field by Management Zone and Nitrogen Rate

Management Zone	Profit – Maximum Nitrogen Rate		Profit – Farmer Practice Nitrogen Rate		Profit – Minimum Nitrogen Rate		Profit – No Nitrogen Applied	
	Mean	Std	Mean	Std	Mean	Std	Mean	Std
Both Hybrids – Mostly A	352.69	49.86	178.45	43.13	93.4	49.86	-132.97	49.86
Both Hybrids – Mostly B	186.63	53.75	113.06	51.19	0.62	53.75	-131.23	53.75
Hybrid A – High Pop	253.32	38.91	223.78	26.87	158.74	38.91	-410	38.91
Hybrid A – Low Pop	301.47	43.44	218.29	30.18	102.06	43.44	-180.08	43.44
Hybrid A – Medium Pop	309.83	46.98	225.8	26.65	112.33	46.98	-295.15	46.98
Hybrid B – High Pop	219.11	80.71	98.14	61.51	-68.12	80.71	-58.37	80.71
Hybrid B – Low Pop	276.14	80.59	132.78	75.06	122.11	80.59	131.86	80.59
All	**290.04**	57.50	**211.79**	46.53	**108.64**	66.12	**-256.49**	125.50

This particular field shows exceptional returns when using 28% UAN in a sidedress application. Expected profit from each grid is expected to be three times of what it would be without using the sidedress application from NDVI data. Additionally, if the grower had applied the maximum nitrogen rate in each zone, additional profitability would have increased around $80 per acre that shows the grower could have placed additional nitrogen on the field and received a greater return. Interestingly enough, the grower could have severely limited profitability and yield if there was not an application of nitrogen in season. The yields from the zero nitrogen application would have been half of what they were in the lowest rate category with a much larger amount of risk based on the value of the standard deviation in profitability of the field.

4.4. Costs of UAS Ownership and Operation

One item that is important to determining whether or not to adopt a new technology is its overall cost to make the investment. Remote sensing with drones is no exception to the rule. For this example, the researcher will be using the cost for a Sentera PHX Pro UAV used for agricultural purposes (Sentera, 2018b). The drone will be carrying the Sentera Double 4K Ag Sensor allowing the grower to take RGB and NDVI imagery. With the drone package, the grower will also need to invest in Sentera's FieldAgent software, which permits the grower to plan flights, view RGB and NDVI imagery through a live feed, and perform other imagery analytics (Sentera, 2018a). This software lets the grower upload the imagery to the FieldAgent software where it can be stitched together and a nitrogen sidedress prescription can be built. The drone itself will be depreciated over three years using the straight-line depreciation method. It is expected the drone and sensor could last longer than three years, but technology with UAS are rapidly evolving and it is expected that a superior UAV would be available at the end of the three years and the grower would choose to upgrade to a newer model. All costs related to owning and operating a drone of this type are summarized in Table 4.13.

These costs are relatively easy to identify, but other costs also need to be estimated to make sure the grower is accounting for all expenses related to gathering the NDVI data. Some of these other costs include labor, maintenance, and insurance. Labor is one of the costs that is necessary to make the drone fly because drones are not fully autonomous at this time. Payscale, Inc. (2018) estimates the average pay for a commercial drone pilot is $35 per hour. For the purposes of this research, the assumption will be made that the pilot will also receive some overtime and there are opportunity costs associated with the time to fly the drone, which will move the hourly rate to $50 per hour. Additionally, the grower will need to pay other costs with employment like FICA taxes, insurance, and training which account for about fifty percent of the hourly rate. Also, the assumption will be made that it takes a total of two hours for the entire process of travel, setup, flight, take down, and uploading data for a 100 acre field. Maintenance costs are estimated to be twenty percent of the total annual depreciation and are based on results from actual UAV pilots (Australian UAV, 2017). Lastly, insurance costs are an important factor and options include liability only or combination hull and liability insurance. Making the assumption the grower would want hull insurance with the liability, insurance would cost around $1,950 on an annual basis with up to $10,000 in physical damage and two million dollars in liability insurance (UAV Coach, 2018). All costs related to owning and operating a drone of this type are summarized in Table 4.13.

Table 4.13. UAV Ownership and Operation Costs

Item	**Cost**	**1,000 Acre Use**	**Description**
Sentera PHX Pro	$ 8,499	$ 2.83	Total Purchase Cost, Over 3 Years and 1,000 Acres
Maintenance	$ 567	$ 0.57	20% Annual Depreciation Over 1,000 Acres
FieldAgent Subscription	$ 1,000	$ 1.00	Annual Cost
Labor	$ 50	$ 1.00	Hourly Rate, Two Hours per 100 Acres Flown
FICA, Taxes, Training	$ 25	$ 0.50	50% of Hourly Pay Rate
Stitching & Rx Cost	$ 7	$ 7.00	Per Acre Cost
Insurance	$ 1,950	$ 1.95	Annual Cost
Total		**$ 14.85**	

Figuring the total costs per acre for drone ownership and operation require one key assumption, the amount of acres flown per year. The researcher in this case expected 1,000 acres to be flown per year. This amount would give the average farm in North Dakota one flight for their corn and wheat acres. Making this assumption, the total costs would be $14.85 per acre. Obviously, with more acres flown, the average cost decreases and begins to approach seven dollars per acre (the cost of stitching and prescription writing per acre charged by Sentera). This would be where the grower would need to make the choice between using a consultant to fly the fields or make the purchase. On these assumptions, the grower would hire the work done by a consultant if they charged less than the $14.85 per acre cost of ownership.

4.5. Overall Results

This next section of this chapter will cover the overall results of the study and determine the profitability of using UAV technology and NDVI imagery together with VRT technology to increase profitability on a growers operation.

The OLS model used in this study has a couple items that need to be discussed. First, looking at the tables for the regression estimates or each field, most of the variables are significant, but overall, the adjusted R^2 values are relatively low. This would lend itself to showing the model is biased and some variables correlated to yield are omitted. Going back to the empirical model, we see there is variable *O* that includes other items the producer cannot control and a variable *CI* the producer can control, but the researcher does not have full knowledge of the components in this variable. These variables were not included in our estimate and would have great impact on yield, leading to the implication that there would be some bias in the model (Pindyck & Rubinfeld, 1997). Secondly, this model does not take in mind that there are spatial correlations between each of the fishnet grids located in the fields. This might lend itself to using a different type of model, such as a spatial model, to estimate the effects on yield.

This next portion will begin with summarizing all of the field level data into one table shown in Table 4.13.

Table 4.14. Summary of Field Profitability Data

Field	Profit – Maximum Nitrogen Rate		Profit – Farmer Practice Nitrogen Rate		Profit – Minimum Nitrogen Rate		Profit – No Nitrogen Applied	
	Mean	Std	Mean	Std	Mean	Std	Mean	Std
Chuck North	171.04	38.27	161.46	39.96	150.31	39.10	81.84	32.14
Faught	-9.40	48.73	-19.39	50.59	-30.86	50.31	-124.09	45.61
Junkyard	96.55	54.60	32.88	79.17	-63.49	126.49		
Kingsley	76.62	55.12	46.30	38.98			36.20	36.65
Raatz	123.28	113.07	112.87	115.06	98.02	112.19	24.49	98.53
Tree Grove	290.04	57.50	211.79	46.53	108.64	66.12	-256.49	125.50
Average	**124.69**	61.22	**90.99**	61.72	**52.52**	78.84	**-47.61**	67.69

Looking at the summary of the field level data shows very interesting results. First, just by making an in-season nitrogen application to the field, the research shows that there are definite advantages to using these technologies, around a $100 per acre return when compared to using the minimum application rates in each part of the field. This means that a grower should adopt the technology if it will cost him or her less than $100 per acre. In all cases, adopting the technology, even in the lowest sense, would provide the grower a net positive return. Secondly, adopting the technology for the grower is a risky decision. In general, looking at the variability of profits for instances where in-season fertilizer was applied shows that profits will vary much more compared to making no applications of nitrogen. Looking at the differences in the standard deviations from the no profit treatment per field and comparing those to the standard deviation of treatments where applications were made reveal this variation. The average value of the standard deviation for all the fields is skewed because of the high variability in the Tree Grove field. Summarizing these two points could be done in one statement, making no applications of in-season nitrogen will consistently provide lower returns per acre. Thus, drone-based remote sensing technology can be used effectively to determine nutrient needs for plants during the growing season in terms of profitability.

One aspect the grower must also analyze is the Return on Investment (ROI) received from investing in a new technology. Using the field level data and the costs of ownership and operation of drones, we can calculate the overall ROI. Assuming the average return from making a sidedress application verses not making a sidedress application is $100.13 per acre and the drone costs of $14.85, the ROI would be 675%. This ROI is very large and would suggest a grower should invest in this technology as soon as possible, but this technology is not being adopted as fast as one would expect.

First, sidedress applications in the state of North Dakota would be an entire culture change. Most growers are not making sidedress applications and would need to make major changes in their operations to switch to this method of applying nitrogen fertilizer. With the short growing season and limited window to make the applications when weather is a major concern, missing the sidedress window could cause huge reductions in revenues and increased costs, further compounding the situation. Second, taking a look at the 2017 growing season (Faught field), net returns for growing corn were negative even if the grower would have sidedressed to the maximum rates. In years like this, the ability to borrow money to invest in such technologies will be limited and growers will need to focus on minimizing losses. Third, sidedress applications and adopting these technologies seem to show greater volatility in profits than making one single nitrogen application, with the exception of the Tree Grove field.

As seen, adopting the technologies in combination should be done at the grower level in many situations. The next question to answer would be, how should the grower adopt the technology, using a consultant or by purchasing the UAV and processing equipment on their own. Each decision has its own unique challenges and benefits, which a grower will have to weigh before making the choice. On the side of purchasing, the cost of getting all the technologies can be relatively expensive when you consider the drone, sensor, processing technology, and prescription writing technologies. When looking at a drone, technology is changing so rapidly in that market that a drone is outdated by the time the grower even opens the box. Additionally, each grower will have to determine if they have enough time available to fly their fields when the sensing should be completed knowing that flying is very time intensive. Lastly, not every grower will have the abilities to understand the data being collected to make the proper decisions as to where to apply the fertilizer within the field. Shown in the data, not making the proper decision can have great impacts on profitability and even greater impact on opportunity costs. On the other hand, paying a consultant can offer its own challenges. Paying for each flight on a field can cost a great deal of money and there is also the possibility that the grower might not be able to get the proper information needed in a timely manner if the consultant overbooks or has delays in collecting or processing the data.

Ultimately, this study has shown that there are definite advantages to using drone-based sensor technology to determine yield and to make recommendations for in-season nitrogen applications. Even with some of the given challenges, growers should consider adopting remote sensing technology and sidedress applications if they want to increase profitability in their operations and become better environment stewards.

5. IMPLICATIONS, LIMITATIONS, AND CONCLUSIONS

This final chapter will cover some of the implications of the study, along with some limitations and needs for further research. As seen in the previous chapter, there is definitely a purpose for using drone and remote sensing technologies to determine in-season fertilizer application needs. It was shown that profitability can be greatly increased when these technologies are used in conjunction with each other, but there are still some additional issues which need to be researched.

5.1. Implications

The research conducted in this study will undoubtedly be listed along with the other studies using NDVI in the industry with similar results as many of the other studies. Looking at the results from the regressions from each particular field, most of the NDVI regression beta values show a positive relationship between NDVI and yield. This is especially true with the second and third sensing dates on the fields planted to corn, but the estimates for yield were far from perfect. As noted in other studies referenced in Chapter 2, NDVI does have its limitations, which may be shown in this model where atmospheric and soil reflectance issues might impact its ability to predict yield. It raises the question as to whether or not other vegetation indices might be better used in determining yield and in-season nitrogen recommendations.

One of the goals of precision agriculture is to have “better management of farm inputs such as fertilizers, herbicides, seed, fuel (used during tillage, planting, spraying, etc.) by doing the right management practice at the right place and the right time” (Mulla, 2013, p. 358). Each of the three “right” statements in the definition show a few items the grower can change to meet the better management option. First, the “right management practice” indicates that the grower can use different methods of managing his or her field by changing tillage practices, adopting precision agriculture techniques to manage the fields, farming methods such as organic vs. conventional farming, or changing the way fertilizers and pesticides are applied. The "right place" statement implies there is variability within the field from space to space. Finally, the "right time" statement directs one to the idea that some of this variability changes over time. Each of the above will be discussed in relation to this study.

The "right management practice" used in this study is two-fold. First, the grower will need to decide to make the change using drone NDVI imagery to make management decisions. Once this decision has been made, the grower will also need to change his or her management practices from making one or a series of flat-rate nitrogen applications to making at least one variable-rate sidedress nitrogen application. Both decision help the grower better manage their inputs.

The spatial aspect of precision agriculture is one of the biggest drivers of why growers would decide to move to managing their fields in this manner. As seen in figure 4.1, there is a large amount of variability across the field. Some of the variability is significant moving from one place to another, like where a red portion is completely surrounded by darker greens. This would lend itself to using a spatial econometric model to estimate yields because there are high correlations between each individual fishnet block located in the field. Ultimately, a grower should try to reduce this variability or determine how best to create profit in the areas where the field varies to a large degree.

The temporal aspect of precision agriculture is also two-fold. First, the grower can use this technology to help improve yields in the short run by making applications which will help increase profitability. As was noted in section 4.4 above, there are definite returns to the grower by making an in-season sidedress application of nitrogen. On the other hand, growers should be working to manage these fields and to reduce variability of the field over the long run to make profitability higher and more constant for the grower. Still using the assumption that the grower is risk-neutral, he or she would most likely accept higher and more consistent returns with less risk.

5.2. Limitations and Need for Further Research

First, this study only looked at two different crops grown in North Dakota on a limited number of fields in this area. Further research should be done on a greater scale and in a number of different areas.

Secondly, more control should have been done with the cooperating growers to insure the yield data received in each case was correct through the calibration of the combines and setting of proper flows. Additionally, other data collected by the growers could have proven useful when determining yield such as as-applied data and basic farm management options such as types of fertilizer, typical tillage types, etc. With more accurate data, the results of the study would have most likely been even more striking.

Thirdly, data collected from the drone was only done a small number of times for each field. This study was not necessarily trying to determine the optimal time for using NDVI imagery within the two crops studied, but it would be nice to have NDVI imagery collected more frequently (i.e., weekly) to determine when the optimal sensing times are for each crop. The researcher understands this will vary from field to field and year to year, but this information will be crucial in making decisions on when to make an in-season application and how much in-season fertilizer to apply. Additionally, the adjusted R^2 values for the regressions are consistent with other published research, but it is believed that better results could have been achieved if the data were collected at different times. Additionally, with more frequent data collection, other vegetation indices could be studied to determine their ability to deal with applying nitrogen fertilizer during the season and their usefulness for determining yield.

Fourth, one question that arises for further research is the proper resolution for NDVI data and its use in estimating yield. In this study, NDVI resolution varied from flight to flight. The question would be, is very high resolution (a few square centimeters) needed when combines that collect the data are collecting, at minimum, 100 square feet per data point? The trend in agriculture is typically to get larger and larger equipment to be more productive which will ultimately reduce data quality because the yield data will come in larger chunks. Lower data quality is opposite of the goal of precision agriculture, so the industry will need to start making determinations in the near future about what is the proper sizing of management zones. The answer maybe that fields need to be managed at larger areas or equipment might need to be redesigned to account for yield data at lower levels.

Fifth, NDVI is a great tool to use for growers to determine vegetation in plants. Further research should be done with plants to decide if this index is the best index to use or if other technologies might provide better insights into plant health and yield potential. Right now, it seems that NDVI is near the top of the list, but the industry should be and is believed to be working on the next technologies that will help make better decisions.

Sixth, growers might choose to invest in a technology even if the expected return is negative. In the case of this study, this could occur when the grower spreads out his or her workload throughout the growing season rather than doing it all in the fall or spring, improving environmental effects, or the ability to receive lower input prices during the growing season. Research should be conducted to determine values for the more intangible items associated with adopting these technologies.

Seventh, as noted prior, it is profitable for a grower to adopt this technology on a per acre basis. A question that should be addressed by the grower is whether it is better for the grower to purchase this technology on his or her own, purchase the technology with another grower, or to rent/lease the technology. This particular question was not addressed in this study, but would be an interesting topic for further research. Some issues which should be weighed against each other would be total amount of acres covered in a year; the need for this technology all at the same time, similar to the need of harvest equipment or planting equipment during the growing season; and the cost benefits of each proposal. It would be expected there are some economies of scale in an instance where equipment sharing is used. The researcher would need to focus on total field capacity and efficiency of the drone sensing technology as described in Hanna (2016). Theoretical framework for this decision could be addressed based on the finding from Artz, Colson, & Ginder's (2010) surveys on group equipment sharing.

Eighth, ROI found in this paper suggests nearly all growers should adopt UAV sensing technologies and in-season sidedress applications, but adopt rates of these technology do not indicate growers have made this decision. Further research on actual adoption rates and reasons why growers are not adopting this technology should be conducted.

5.3. Conclusions

Drone technology is definitely one technology that will be used in agriculture for years to come especially as some of the challenges of using drones are answered. Some of these challenges include using drones in beyond line of site applications, making the drones completely autonomous where data can be collected without using much labor, and understanding the relationships between plant growth and sensing technology.

REFERENCES

AgEagle Aerial Systems (2016). *Compare AgEagle models*. Retreived from http://ageagle.com/compare/

Ag Leader (2017). SMS Advanced 17.5 [Computer software]. Ames, IA.

Andrade-Sanchez, P. & Heun J.T. (2010). *Things to know about applying precision agriculture technologies in Arizona* (Bulletin AZ1535). Tuscon, AZ: The University of Arizona - Cooperative Extension.

Arnall, D. B., Tubaña, B. S., Holtz, S. L., Girma, K., & Raun, W. R. (2009). Relationship between nitrogen use efficiency and response index in winter wheat. *Journal of Plant Nutrition 32*(3), 502-515. doi: 10.1080/01904160802679974

Artz, G. M., Colson, G., & Ginder, R. (2010). A return of the threshing ring? A case study of machinery and labor-sharing in Midwestern farms. *Journal of Agricultural and Applied Economics, 42*(4), 805–819. doi: 10.1017/S1074070800003977

Australian UAV (2017). *Drones: Total Cost of Ownership (TCO).* Retrieved from https://www.auav.com.au/articles/drones-total-cost-ownership-tco/

Avanzini, G., de Angelis, E. L., & Giulietti, F. (2016). Optimal performance and sizing of a battery-powered aircraft. *Aerospace Science and Technology 59*, 132-144. doi: 10.1016/j.ast.2016.10.015

Badu, S. (2016). *Computing the yield per acre for a given field using GIS capabilities* (Masters thesis). Retrieved from https://library.ndsu.edu/ir/handle/10365/25888

Bauer, M. E., & Cipra, J. E. (1973). *Identification of agricultural crops by computer processing of ERTS MSS data* (LARS Technical Reports, Paper 20). Retrieved from http://docs.lib.purdue.edu/larstech/20

Berg, N. (2017). *UAS Drone Presentation*. Presentation at the Precision Ag Summit, Jamestown, ND. Retrieved from http://theresearchcorridor.com/precisionagsummit2017/presentations

Bharathkumar, L. & Mohammed-Aslam, M. A. (2015). Crop pattern mapping of Tumkur Taluk using NDVI technique: A remote sensing and GIS approach. *Aquatic Procedia 4,* 1397-1404. doi: 10.1016/j.aqpro.2015.02.181

Biermacher, J. T., Epplin, F. M., Brorsen, B. W., Solie, J. B., & Raun, W. R. (2009). Economic feasibility of site-specific optical sensing for managing nitrogen fertilizer for growing wheat. *Precision Agriculture, 10*(3), 213-230. doi: 10.1007/s11119-008-9092-y

Bullock, D. G. & D. S. Bullock. (1994). Quadratic and quadratic-plus-plateau models for predicating optimal nitrogen rate of corn: A comparison. *Agronomy Journal 86*(1), 191-195. doi: 10.2134/agronj1994.00021962008600010033x

Bullock, D. S., Lowenberg-Deboer, J., & Swinton, S. M. (2002). Adding value to spatially managed inputs by understanding site-specific yield response. *Agricultural Economics*, *27*(3), 233–245. doi: 10.1016/S0169-5150(02)00078-6

Bullock, D. S., Ruffo, M. L., Bullock, D. G., & Bollero, G. A. (2009). The value of variable rate technology: An information-theoretic approach. *American Journal of Agricultural Economics 91*(1), 209–223. doi: 10.1111/j.1467-8276.2008.01157.x

Buttafuoco, G., Castrignanò, A., Cucci, G., Lacolla, G., & Lucà, F. (2017). Geostatistical modelling of within-field soil and yield variability for management zones delineation: A case study in a durum wheat field. *Precision Agriculture 18*(1), 37-58. doi: 10.1007/s11119-016-9462-9

Colwell, R. N. (1956). Determining the prevalence of certain cereal crop diseases by means of aerial photography. *Hilgardia, 26*(5), 223-286. doi: 10.3733/hilg.v26n05p223

Crusiol, L. G. T., Carvalho, J. F. C., Sibaldelli, R. N. R., Neiverth, W., Rio, A., Ferreira, L. C., …, Farias, J. R. B. (2017). NDVI variation according to the time of measurement, sampling size, positioning of sensor and water regime in different soybean cultivars. *Precision Agriculture 18*(4), 470-490. doi: 10.1007/s11119-016-9465-6

DJI (2017a). *Matrice 600 Pro Specs*. Retrieved from https://www.dji.com/matrice600-pro/info#specs

DJI (2017b). *Phantom 4 Specs*. Retrieved from https://www.dji.com/phantom-4/info#specs

Erickson, B. & Widmar, D. A. (2015). *2015 Precision agricultural services dealership survey results.* West Lafayette, IN: Department of Agricultural Economics, Purdue University. Retreived from http://agribusiness.purdue.edu/files/resources/2015-crop-life-purdue-precision-dealer-survey.pdf

ESRI (2015). ArcMap 10.4.1 [Computer software]. Redlands, CA.

Estel, S., Kuemmerle, T., Alcántara, C., Levers, C., Prishchepov, A., & Hostert, P. (2015). Mapping farmland abandonment and recultivation across Europe using MODIS NDVI time series. *Remote Sensing of Environment 163*, 312-325. doi: 10.1016/j.rse.2015.03.028

FAA (2016). *Summary of small unmanned aircraft rule (Part 107)*. Retrieved from https://www.faa.gov/uas/media/Part_107_Summary.pdf

FAA (2017). *FAA DroneZone.* Retrieved from https://registermyuas.faa.gov/

Fairchild, D. S. (1988). Soil information system for farming by kind of soil. *Proceedings from the International Interactive Workshop on Soil Resources: Their Inventory, Analysis and Interpretations for Use in the 1990's*, 159-164. St. Paul, MN: University of Minnesota.

Fan, X. & Liu, Y. (2017). A comparison of NDVI inter-calibration methods. *International Journal of Remote Sensing 38*(19), 5273-5290. doi: 10.1080/01431161.2017.1338784

Food and Agriculture Organization of the United Nations (2009). *How to feed the world in 2050* (Issue Brief). Retrieved from http://www.fao.org/fileadmin/templates/wsfs/docs/expert_paper/How_to_Feed_the_World_in_2050.pdf

Food Security and Nutrition Analysis Unit (n.d.). *Understanding the Normalized Difference Vegetation Index (NDVI).* Retrieved from http://www.fsnau.org/downloads/Understanding_the_Normalized_Vegetation_Index_NDVI.pdf

Fortes, R., Prieto, M. H., García-Martín, A., Córdoba, A., Martínez, L., & Campillo, C. (2015). Using NDVI and guided sampling to develop yield prediction maps of processing tomato crop. *Spanish Journal of Agricultural Research 13*(1), 1-9. doi: 10.5424/sjar/2015131-6532

Franzen, D. (2013, June 13). Topdress and sidedress options for solid-seeded and row crops. *Crop and Pest Report*. Retrieved from https://www.ag.ndsu.edu/cpr/soils/topdress-and-sidedress-options-for-solid-seeded-and-row-crops-06-06-13

Gago, J., Douthe, C., Coopman, C. E., Gallago, P. P., Ribas-Carbo, M., Flexas, J., . . ., Medrano, H. (2015). UAVs challenge to assess water stress for sustainable agriculture. *Agricultural Water Management 153.* 9-19. doi: 10.1016/j.agwat.2015.01.020

Hanna, M. (2016). *Estimating the field capacity of farm machines.* (Iowa State University Ag Decision Maker Information Files, A3-24). Ames, IA. Retrieved from http://lib.dr.iastate.edu/pubs_agdm/8

Haugen, R. (2017). *Custom farm work rates on North Dakota farms, 2016.* (NDSU Extension Publication EC499). Fargo, ND. Retrieved from https://www.ag.ndsu.edu/publications/farm-economics-management/custom-farm-work-rates-on-north-dakota-farms-2016/ec499.pdf

Huang, J., Wang, X., Li, X., Tian, H., Pan, Z. (2013). Remotely sensed rice yield prediction using multi-temporal NDVI data derived from NOAA's-AVHRR. *PLoS ONE 8*(8): e70816. doi: 10.1371/journal.pone.0070816

Ireland-Otto, N., Ciampitti, I. A., Blanks, M. T,. Burton, Jr., R. O., & Balthazor, T. (2016). Costs of using unmanned aircraft on crop farms. *2016 Journal of the ASFMRA.* Retrieved from http://ageconsearch.umn.edu/bitstream/236660/2/439-Otto.pdf

Jenkins, D. & Vasigh, B. (2013). *The economic impact of unmanned aircraft systems integration in the United States.* Arlington, VA: Association for Unmanned Vehicle Systems International. Retrieved from http://www.auvsi.org/our-impact/economic-report

Johnson, C. E., Schafer, R. L. & Young, S. C. (1983). Controlling agricultural machinery intelligently: Agricultural electronics - 1983 and beyond. *Proceedings of the National Conference on Agricultural Electronics Applications*, 114-119. St. Joseph, MI: American Society of Agricultural Engineers.

Jones, J. R., Fleming, C. S., Pavuluri, K., Alley, M. M., Reiter, M. S., & Thomason, W. E. (2015). Influence of soil, crop residue, and sensor orientations on NDVI readings. *Precision Agriculture 16*(6), 690-704. doi: 10.1007/s11119-015-9402-0

Know Before You Fly (2017a). *Business Users*. Retrieved from http://knowbeforeyoufly.org/for-business-users/

Know Before You Fly (2017b). *Educational Use*. Retrieved from http://knowbeforeyoufly.org/education-use/

Know Before You Fly (2017c). *Introduction.* Retrieved from http://knowbeforeyoufly.org/

Know Before You Fly (2017d). *Public Entities*. Retrieved from http://knowbeforeyoufly.org/for-public-entities/

Know Before You Fly (2017e). *Recreational Users.* Retrieved from http://knowbeforeyoufly.org/for-recreational-users/

Larson, J. A., Roberts, R. K., English, B. C., Cochran, R. L., & Wilson, B. S. (2005). A computer decision aid for the cotton yield monitor investment decision. *Computers and Electronics in Agriculture 48*(3), 216-234. doi: 10.1016/j.compag.2005.04.001

Legg, B. J. & Stafford, J. V. (1998). Precision agriculture – new technologies. *Proceedings of the Brighton Crop Protection Conference - Pests & Diseases*, 1143-1150. Hampshire, Great Britain: British Crop Protection Council.

Liu, H. Q., & Huete, A. (1995). A feedback based modification of the NDVI to minimize canopy background and atmospheric noise. *IEEE Transactions on Geoscience and Remote Sensing, 33*(2), 457-465. doi: 10.1109/36.377946

Louargant, M., Villette, S., Jones, G., Vigneau, N., Paoli, J. N., & Gée, C. (2017). Weed detection by UAV: Simulation of the impact of spectral mixing in multispectral images. *Precision Agriculture 18*(6), 932-951. doi: 10.1007/s11119-017-9528-3

Lowenberg-DoBoer, J. (1999). Risk Management Potential of Precision Farming Technologies. *Journal of Agriculture and Applied Economics 31*(2), 275-285. doi: 10.1017/S1074070800008555

Magney, T. S., Eitel, J. U. H., Huggins, D. R., & Vierling, L. E. (2016). Proximal NDVI derived phenology improves in-season predictions of wheat quantity and quality. *Agricultural and Forest Meteorology 217*, 46–60. doi: 10.1016/j.agrformet.2015.11.009

Magney, T. S., Eitel, J. U. H., & Vierling, L. E. (2017). Mapping wheat nitrogen uptake from RapidEye vegetation indices. *Precision Agriculture 18*(4), 429-451. doi: 10.1007/s11119-016-9463-8

Mamo, M., Malzer, G. L., Mulla, D. J., Huggins, D. J., & Strock, D. (2003). Spatial and temporal variation in economically optimum N rate for corn. *Agronomy Journal 95*(4), 958-964. doi: 10.2134/agronj2003.0958

Mazza, E. (2015, November 30). See the Amazon drone that will deliver in 30 minutes or less. *Huffington Post*. Retrieved from http://www.huffingtonpost.com/entry/amazon-prime-air-drone-video_565be125e4b079b2818abd55

McSweeny, K. (2016, September 2). Autonomous tractors could turn farming into a desk job. *ZDNet*. Retrieved from http://www.zdnet.com/article/autonomous-tractors-could-turn-farming-into-a-desk-job/

Mekliche, A., Hanifi-Mekliche, L., Aïdaoui, A., Gate, P., Bouthier, A., & Monneveux, P. (2015). Grain yield and its components study and their association with normalized difference vegetation index (NDVI) under terminal water deficit and well-irrigated conditions in wheat (*Triticum durum* Desf. and *Triticum aestivum* L.). *African Journal of Biotechnology 14*(26), 2142-2148. doi: 10.5897/AJB2015.14535

Miao, Y., Mulla, D. G., Randall, G. Vetsch, J. & Vintila, R. (2009). Combining chlorophyll meter readings and high spatial resolution remote sensing images for in-season site-specific nitrogen management of corn. *Precision Agriculture 10*(1), 45-62. doi: 10.1007/s11119-008-9091-z

MicaSense (2017). *Introducing RedEdge-M*. Retrieved from https://www.micasense.com/rededge-m

Mkhabela, M. S., Bullock, P., Raj, S., Wang, S., & Yang, Y. (2011). Crop yield forecasting on the Canadian Prairies using MODIS NDVI data. *Agricultural and Forest Meteorology 151*(3), 383-393. doi: 10.1016/j.agrformet.2010.11.012

Mulla, D. J. (2013). Twenty five years of remote sensing in precision agriculture: Key advances and remaining knowledge gaps [Special Issue]. *Biosystems Engineering 114*, 358-371. doi: 10.1016/j.biosystemseng.2012.08.009

Nguy-Robertson, A., Brinley-Buckley, E., Suyker, A., Awada, T. N. 2016. Determining factors that impact the calibration of consumer-grade digital cameras used for vegetation analysis. *International Journal of Remote Sensing, 37*(14), 3365-3383. doi: 10.1080/01431161.2016.1199061

Nowatzki, J. & Hofman, V. (2009). *Variable-rate fertilization for field crops equipment requirements* (Publication number AE-1445). Fargo, ND: North Dakota State University Extension Service.

Ortiz, B., Shaw, J. N., & Fulton, J. (2011). *Basics of crop sensing* (Publication No. ACES-1398). Auburn, AL: Alabama Cooperative Extension System

Parrot SA (2017a). *Parrot Sequoia.* Retrieved from https://www.parrot.com/us/business-solutions/parrot-sequoia#parrot-sequoia-

Parrot SA (2017b). *Parrot Sequoia Technical Specifications*. Retrieved from https://www.parrot.com/us/business-solutions/parrot-sequoia#technicals

Payscale, Inc. (2018). Drone pilot salary. Retrieved from https://www.payscale.com/research/US/Job=Drone_Pilot/Hourly_Rate

Pereira, R. M., Casaroli, D., Vellame, L. M., Alves, Jr., J., & Evangelista, A. W. P. (2016). Sugarcane leaf area estimate obtained from the corrected Normalized Difference

Vegetation Index (NDVI). *Agricultural Research in the Tropics 46*(2), 140-148. Retrieved from http://www.scielo.br/pdf/pat/v46n2/1983-4063-pat-46-02-0140.pdf

Pindyck, R. & Rubinfeld, D. (1997). *Econometric models and economic forecasts* (4th ed). Boston, MA: Irwin/McGraw-Hill.

Pix4D [Computer software]. Retrieved from www.pix4d.com

Raun, W. R., Solie, J. B., Johnson, G. V., Stone, M. L., Lukina, E. V., Thomason, W. E., Schepers, J. S. (2001). In-season prediction of potential grain yield in winter wheat using canopy reflectance. *Agronomy Journal, 93*(1), 131–138. doi: 10.2134/agronj2001.931131x

Raun, W. R., Solie, J. B., Johnson, G. V., Stone, M. L., Mullen, R. W., Freeman, K. W., . . . Lukina, E. V. (2002). Improving nitrogen use efficiency in cereal grain production with optical sensing and variable rate application. *Agronomy Journal 94*(4), 815-820. doi: 10.2134/agronj2002.0815

Raun, W. R., Solie, J. B., & Stone, M. L. (2011). Independence of yield potential and crop nitrogen response. *Precision Agriculture 12*(4), 508-518. doi: 10.1007/s11119-010-9196-z

Raven Industries (n.d.) *Hawkeye Nozzle Control.* Retrieved from https://ravenprecision.com/products/application-controls/hawkeye-nozzle-control

Roberts, D. C., Brorsen, B. W., Solie, J. B., & Raun, W. R. (2013). Is data needed from every field to determine in-season precision nitrogen recommendations in winter wheat? *Precision Agriculture 14*(3): 245-269. doi: 10.1007/s11119-012-9291-4

Rouse, Jr., W., Haas, R. H., Schell, J. A., & Deering, D. W. (1974). *Monitoring vegetation systems in the Great Plains with ERTS* (Publication No. A 20). College Station, TX:

Remote Sensing Center, Texas A&M University. Retrieved from https://ntrs.nasa.gov/archive/nasa/casi.ntrs.nasa.gov/19740022614.pdf

Ruffo, M. L., Bollero, G. A., Bullock, D. S., & Bullock, D. G. (2006). Site-specific production functions for variable rate corn nitrogen fertilization. *Precision Agriculture, 7*(5), 327–342. doi: 10.1007/s11119-006-9016-7

SAS Institute (2013). SAS 9.4 [Computer software]. Cary, NC.

Schimmelpfenning, D. (2016). *Farm profits and adoption of precision agriculture* (USDA ERS Publication No. ERR-217). Washington, DC: U.S. Government Printing Office.

Schimmelpfenning, D. & Ebel, R. (2016). Sequential adoption and cost savings from precision agriculture. *Journal of Agricultural and Resource Economics 41*(1), 97–115.

Searcy, S. W. (1997). *Precision farming: A new approach to crop management* (Publication No. L-5177). College Station, TX: Texas Agriculture Extension Service.

Searcy, S. W., Schueller, J. K., Bae, Y. H., Borgelt, S. C., & Stout, B. A. (1989). Mapping of spatially variable yield during grain combining. *Transactions of the American Society of Agricultural Engineers, 32*(3), 826-829.

SenseFly (2017). *eBee: The professional mapping drone*. Retrieved from https://www.sensefly.com/drones/ebee.html

Sentera (2017a). *High precision single sensors data sheet* (Lit. 4064). Retrieved from https://sentera.com/wp-content/uploads/2017/05/Single_NDRE_NDVI_Lit4064_WEB.pdf

Sentera (2017b). *High precision single sensors quantum efficiency curves* (Lit. 4065A). Retrieved from https://sentera.com/wp-content/uploads/2017/07/QE_single_Lit4065A.pdf

Sentera (2018a). *FIELDAGENT™ platform* (Lit. 4079). Retrieved from https://sentera.com/wp-content/uploads/2018/01/FieldAgent_Lit4079.pdf

Sentera (2018b). *Sentera PHX UAV* (Lit. 4060B). Retrieved from https://sentera.com/wp-content/uploads/2018/01/PHX_Lit4060B_Sentera.pdf

Shrestha, R., Di, L., Yu, E. G., Kang, L., Yuan-zheng, S., & Yu-qi, B. (2017). Regression model to estimate flood impact on corn yield using MODIS NDVI and USDA cropland data layer. *Journal of Integrative Agriculture 16*(2), 398–407. doi: 10.1016/S2095-3119(16)61502-2

Simelli, I. & Tsagaris, A. (2015). The use of unmanned aerial systems (UAS) in agriculture. *Proceedings of the 7th International Conference on Information and Communication Technologies in Agriculture*, 730-736. Kavala, Greece.

Sruthi, S. & Mohammed-Aslam, M. A. (2015). Agricultural drought analysis using the NDVI and land surface temperature data: A case study of Raichur District. *Aquatic Procedia 4*, 1258-1264. doi: 10.1016/j.aqpro.2015.02.164

Stafford, J. V. (2000). Implementing precision agriculture in the 21st century. *Journal of Agricultural Engineering Research 76*(3), 267-275. doi: 10.1006/jaer.2000.0577

Stafford, J. V. & Ambler, B. (1994). In-field location using GPS for spatially variable field operations. *Computers and Electronics in Agriculture 11*(1), 23-26. doi: 10.1016/0168-1699(94)90050-7

Stafford, J. V., Ambler, B., & Smith, M. P. (1991). Sensing and mapping grain yield variation. Proceedings from Symposium *Automated Agriculture for the 21st Century*, 356-365. St. Joseph, MI: American Society of Agricultural Engineers.

Stefanini, M. R. (2015). *Effects of optical sensing and variable rate technology on nitrogen fertilizer use, lint yields, and profitability in cotton production* (Masters thesis). Retrieved from Tennessee Research and Creative Exchange. (3515)

Steven, M. D. (1993). Satellite remote sensing for agricultural management: opportunities and logistic constraints. *ISPRS Journal of Photogrammetry and Remote Sensing 48*(4), 29-34. doi: 10.1016/0924-2716(93)90029-M

Suddoth, K. A., Drummond, S. T., & Myers, D. B. (2012). *Yield Editor 2.0: Software for automated removal of yield map errors.* Paper presented at the 2012 American Society of Agricultural and Biological Engineers Annual International Meeting. ASABE Paper 121338343. St. Joseph, MI: ASABE. Retrieved from http://extension.missouri.edu/sare/documents/ASABEYieldEditor2012.pdf

Sugiura, R., Noguchi, N., & Ishii, K. (2005). Remote-sensing technology for vegetation monitoring using an unmanned helicopter. *Biosystems Engineering 90*(4), 369-379. doi: 10.1016/j.biosystemseng.2004.12.011

Swenson, A. & Haugen, R. (2015a). *Projected 2016 crop budgets: East Central North Dakota*. (NDSU Extension Publication EC1658). Fargo, ND. Retrieved from https://www.ag.ndsu.edu/farmmanagement/documents/eastcentral-2016-budget-1

Swenson, A. & Haugen, R. (2015b). *Projected 2016 crop budgets: South East North Dakota*. (NDSU Extension Publication EC1659). Fargo, ND. Retrieved from https://www.ag.ndsu.edu/farmmanagement/documents/southeast-2016-budget-2

Swenson, A. & Haugen, R. (2017). *Projected 2017 crop budgets: Southern Valley North Dakota*. (NDSU Extension Publication EC1660). Fargo, ND. Retrieved from https://www.ag.ndsu.edu/farmmanagement/documents/17-sv-bud-pdf

Tong, X., Brandt, M., Hiernaux, P., Herrmann, S., & Tian, F., Prishchepov, A., & Fensholt, R. (2017). Revisiting the coupling between NDVI trends and cropland changes in the Sahel drylands: A case study in western Niger. *Remote Sensing of Environment 191*, 286-296. doi: 10.1016/j.rse.2017.01.030

Tucker, C. J. (1978). *Red and photographic infrared linear combinations for monitoring vegetation.* (NASA Technical Memorandum 79620). Greenbelt, MA: National Aeronautics and Space Administration. Retrieved from https://ntrs.nasa.gov/archive/nasa/casi.ntrs.nasa.gov/19780024582.pdf

Tucker, C. J., Holben, B. N., Elgin, Jr., J. H., & McMurtrey III, J. E. (1979). *The relationship of red and photographic infrared spectral data to grain yield variation within a winter wheat field.* (NASA Technical Memorandum 80328). Greenbelt, MA: National Aeronautics and Space Administration. Retrieved from https://ntrs.nasa.gov/archive/nasa/casi.ntrs.nasa.gov/19800004281.pdf

Turner, J. M., Kenkel, P. L., Holcomb, R. B., & Arnall, D. B. (2016). *Economic potential of unmanned aircraft in agricultural and rural electric cooperatives*. Paper presented at the Southern Agricultural Economics Association Annual Meeting. Retrieved from http://purl.umn.edu/230047

UAV Coach (2018). *Drone insurance: A step-by-step guide to liability & drone hull insurance.* Retrieved from https://uavcoach.com/drone-insurance-guide/

USDA ARS (2016). Yield Editor 2.0.7 [Computer software]. Retrieved from https://www.ars.usda.gov/research/software/download/?softwareid=370

USDA NRSC (2017). *Web Soil Survey* [Data set]. Retrieved from SMS Advanced Software.

Vansichen, R. & de Baerdemaeker, J. (1991). Continuous wheat yield measurement on a combine. *Proceedings of Symposium & Automated Agriculture for the 21st Century*, 346-355, St. Joseph, MI: American Society of Agricultural Engineers.

Varvel, G. E., Wilhelm, W. W., Shanahan, J. F., Schepers, J. S. (2007). An algorithm for corn nitrogen recommendations using a chlorophyll meter based sufficiency index. *Agronomy Journal 99*(3), 701-706. doi: 10.2134/agronj2006.0190

Viña, A. Gitelson, A. A., Rundquist, D. C., Keydan, G., Leavitt, B., & Schepers, J. (2004). Monitoring maize (*Zea mays L.*) phenology with remote sensing. *Agronomy Journal 96*(4), 1139-1147. doi: 10.2134/agronj2004.1139

Zhang, Z. T., Lan, Y., Wu, P. T., & Han, W. T. (2014). Model of soybean NDVI change based on time series. *International Journal of Agricultural and Biological Engineering 7*(5), 64-70. doi: 10.3965/j.ijabe.20140705.007