PRECISION AGRICULTURE TECHNOLOGY ADOPTION AND USAGE IN NORTH DAKOTA

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ABSTRACT

The world population is projected to rise, and there is a growing concern of future food availability. Precision agriculture technologies are one solution to this problem as they aim to produce more food on less land. This study examines the adoption and intensity of precision agriculture technology usage by producers in North Dakota. Data from a North Dakota State University survey was collected and analyzed using an econometric double-hurdle model. Results of the study describe which producers adopt precision agriculture technologies, which technologies complement each other, and what affects the intensity of technology usage. Several technologies were found to have complementary effects on each other, larger farms are more likely to adopt PATs, and crop choices have varying impacts on the adoption and usage of PATs. Most of these findings agree with previous literature, although new light was shed on some new findings and predictions.

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CHAPTER 1. INTRODUCTION

1.1. Overview

The world population is projected to reach 10 billion people by 2050, which will in turn increase the demand for food and agricultural products (Fess, Kotcon, and Benedito, 2011). There is a global concern with the availability of arable land to provide enough food for the growing population. For example, from 1980 to 2000, the U.S. population grew by 24%, while 34% of arable land and forestland was transformed for urban development (Alig, Kline, and Lichtenstein, 2004). Precision agriculture is one response to these challenges. Today, many farmers are adopting precision agriculture technologies (PAT) with hopes of increasing yields, reducing waste, and decreasing risks associated with farming (Ling and Bextine, 2017).

Precision agriculture technologies are designed to decrease input usage or increase output by farmers, leading to more profitable farms. Technologies such as robots, moisture sensors, temperature sensors, global positioning systems (GPS), and aerial imaging are increasingly common in agriculture. These technologies are generally more efficient and precise than humans, relatively safe, and lead to higher profits for users (Kirkpatrick, 2019).

Using traditional farming methods, decisions such as whether to plant, spray chemical, and harvest are typically made based on the whole field (Ling and Bextine, 2017). With precision farming, decisions are made based on specific areas of a field, sometimes even down to a specific plant. Precision agriculture combines multiple technologies to manage the care plants receive. For example, information about the moisture of soil around a plant, stem size, and leaf shape can be obtained to analyze plant health and stress. After analyzing this information, farmers can deliver the proper nutrients needed to improve health and promote the growth of a specified area (Ling and Bextine, 2017).

Currently, the U.S. agriculture industry is lacking in digitalization relative to other sectors of the U.S. economy (Jarvis, 2017). The current lack of digitalization and precision agriculture technologies are due to expensive initial investment costs, lack of broadband internet in rural areas, and the predominance of older producers who may not be comfortable with all technologies (Ling and Bextine, 2017). The 2017 Census of Agriculture found that 9.2% of agricultural producers are younger than 35 years old (United States Department of Agriculture, 2019a). However, a generational transition is likely to occur in the near future with younger producers taking over farm operations. Young producers who are decision makers tend to have farms that are bigger in both sales and acres (United States Department of Agriculture, 2019a). These young producers likely have more exposure to and knowledge of precision agriculture technologies. Precision agriculture could become more widespread in the near future as broadband internet access is expanding, and next-generation farmers are taking over operations (Ling and Bextine, 2017).

Current precision agriculture technologies could be just the beginning of digitalization of the agriculture industry. GPS guidance and auto-steer technology have become commonplace for large grain farms (Shockley et al., 2011). Similarly, variable rate technology and automatic section control are rapidly gaining popularity. The goal of precision agriculture is to optimize returns from inputs used for production while preserving resources (Borst, 2017). Farmers adopt precision agriculture because it adds value in the form of smarter decision making, which leads to more efficient operation and management of farming practices (Borst, 2017). Overall, precision agriculture technologies are at the forefront of an agriculture revolution due to their ability to increase efficiency and maximize farm profits.

1.2. Problem Statement

Precision agriculture technologies are widely believed to benefit farmers, increase profits, and help provide a sustainable amount of food for a growing population. There are many obstacles to adopting these technologies including ease of use, perceived compatibility, profitability, time constrains, and other factors. The main focus of this study is the hurdle of adopting a precision agriculture technology and the intensity at which an adopted technology is used. While looking into this, the effects that other PATs have on the original PAT will be analyzed to see if any are complementary in nature. This study will look further into other factors that influence adoption such as producer age, education, and farm size.

1.3. Objectives

This study examines the adoption and usage of precision agriculture technologies by farm producers throughout the state of North Dakota. Several studies measure the profitability of certain technologies and literature suggests that some technologies complement each other. However, those studies fail to measure the complementary effects the technologies could have on each other. This study will attempt to measure those effects. The objectives of this study are as follows:

1. Survey North Dakota agricultural producers to measure their current use of precision agriculture technologies.
2. Evaluate the collected data and identify patterns in the adoption and intensity of usage for precision agriculture technologies.
3. Analyze the relationships between different precision agriculture technologies and identify whether and how they are used together.

1.4. Organization of the Study

Chapter 2 introduces and explains the seven precision agriculture technologies analyzed in the study. Chapter 3 discusses literature relevant to the technologies. Chapter 4 reviews the methodology used in the study. Chapter 5 discusses and interprets the empirical results. Lastly, Chapter 6 is the conclusions section, which goes over implications of the results and what further research could be done to improve understanding of this topic.

CHAPTER 2. DESCRIPTION OF PRECISION AGRICULTURE TECHNOLOGIES

This study examines precision agriculture technology (PAT) usage. The precision agriculture technologies considered in this study include global positioning system guidance; auto-steer; automatic section control; satellite imagery; unmanned aircraft systems; variable rate nitrogen application; and variable rate seeding. Each technology provides specific benefits, although some of these benefits may complement the benefits of other PATs.

In general, adoption of PATs varies widely among producers as every operation functions differently and has unique goals. Global positioning system (GPS) guidance is one of the oldest and most commonly used technologies. The U.S. government made GPS signal available for civilian use in 1983. By 2017, manual and automated GPS guidance was used by an estimated 60% of U.S. agricultural producers (Erickson, Lowenberg-DeBoer, and Bradford, 2017). Automated guidance, also known as auto-steer, was used for applying about 40% of agricultural fertilizer and chemicals in the U.S. in 2015 (Lowenberg-DeBoer, 2015). On the other hand, UAS only became available for civilian use in 2012 (Fultz, 2018). Usage of UAS in agriculture was predicted to be just 6% in 2017 (Erickson et al., 2017). This chapter describes the technologies that are analyzed in this study.

2.1. Global Positioning System Guidance

Global positioning system guidance maps precise field locations that are difficult to determine visually, thereby keeping the operator on a straight path while operating (Schimmelpfennig, 2016). GPS guidance technology gives operators access to timely and accurate coordinates on an in-cab screen. Through using this technology, operator errors and fatigue are reduced. In addition, GPS guidance reduces overapplication and underapplication for both seeding and spraying. It also allows the operator to watch the equipment and in-cab monitors more consistently (Schimmelpfennig, 2016). Lightbar guidance is a common example of GPS guidance. Lightbar systems do not steer the tractor, but instead use graphical displays to show if the tractor is off-track (Laws, 2004). Because operators are subject to error, this system is generally less accurate than standard auto-steer systems.

2.2. Auto-Steer

Auto-steer, or automated steering, is a navigation system that uses global positioning systems (GPS) to direct agricultural machinery (Shockley et al., 2011). Operators keep their hands off the wheel while auto-steer is engaged, essentially letting the machinery drive itself (Hill, 2009). With auto-steer technology, operators are still required to navigate around obstacles in the field and make necessary turns. This technology reduces implement overlap, skips, and inward drift while increasing the accuracy of input placement, decreasing operator fatigue, and reducing machinery costs by increasing machinery field capacity (Shockley et al., 2011). Many auto-steer systems and GPS receivers can be used together with varying precision. Bolt-on auto-steer systems with submeter receivers are common because they are relatively low cost, but they are also less accurate than other systems. Integral valve system auto-steer combined with a Real Time Kinematic (RTK) GPS receiver is the most accurate system (Shockley et al., 2011).

2.3. Automatic Section Control

Automatic section control (ASC) is used on planters, sprayers, and fertilizer spreaders to prevent overlap. On a sprayer, automatic section control maps treated areas as the sprayer travels the field (Luck et al., 2011). Along with knowledge of the sprayer geometry and active control sections, the sprayed areas are georeferenced using coordinates generated by the GPS receiver. While the sprayer travels the field, the controller continuously checks to see if any boom sections have passed over previously mapped areas or field boundaries. When a boom section passes into these previously sprayed areas, specific sections of the spray boom will automatically turn off, and they will turn back on when it crosses over to unsprayed areas within the field boundary (Luck et al., 2011). Planters and fertilizer spreaders with automatic section control mimic this same process.

Before section control, an entire spray boom would have to be on just to cover a narrow area of a field. The introduction of manual section control technology allowed operators to turn off specific sections of the spray boom by hand. This technology is useful, but it is difficult for an operator to judge when to shut off sections. Even with manual section control, overlap is common on headlands and around obstacles in the field, as it is difficult for an operator to turn off sections while steering (Luck et al., 2011). ASC was designed to mitigate these problems and reduce input costs on chemicals by decreasing overlap, which can also lead to increased soil productivity. ASC technology has been rapidly advancing and can now be controlled down to individual nozzles that are spaced just inches apart on a sprayer. With fewer chemicals going into the ground, the environmental footprint left behind is reduced, and future crops have the potential to grow healthier (Luck et al., 2011). Section control on planters can reduce seed cost and allow for a more uniform plant population as well as healthier plants. When plants are too close to one another, they compete for nutrients and can have negative effects on each other, reducing yield. Advances in section control technology decrease overlap that previous technologies imposed, can improve soil productivity, and reduces the environmental footprint of chemicals (Luck et al., 2011).

2.4. Satellite Imagery

Satellite imagery technology allows producers to identify and resolve problematic field areas within the growing season by using high resolution images to produce field maps (Yang et al., 2013). Before satellite imagery became prevalent in agriculture, yield monitors were commonly used to collect data after a crop was harvested, which only allows a producer to recognize and fix problematic areas for the next season and does not allow a producer to promote plant growth during the current season. Satellite imagery allows producers to identify nutrient deficiencies, water stress, and pest infestations during the growing season (Yang et al., 2013). Satellite imagery technology has been around for many years, but due to its coarse spatial resolution it has traditionally had little use for assessing within-field variability (Yang et al., 2013). As a result of resolution advancements, satellite imagery can now help farmers manage crops and make changes to promote in-season growth.

2.5. Unmanned Aircraft Systems

Unmanned Aircraft Systems (UAS), or drones, can benefit farmers through soil and crop monitoring, as well as field mapping. Drones can have mounted moisture and nutrient sensors to monitor the ground temperature, moisture, and chemical composition of the soil, which helps to make planting decisions (Fultz, 2018). UAS are used for inspecting, surveying, and observing farmland in a quick and efficient manner to provide greater detail than scouting by foot, vehicle, or from an airplane (Fultz, 2018). Furthermore, UAS can be equipped with a package of high-definition cameras and image-recognition sensors to monitor crops, which can provide significant increases in efficiency (Kirkpatrick, 2019). Drones benefit farmers by potentially increasing yields and reducing labor. Field mapping data helps farmers make informed decisions on the amount of fertilizer to apply and what chemicals to spray. UAS are a relatively cheap precision agriculture technology for a farmer to adopt. A farmer can purchase a drone that is capable of field mapping for under $1,000, whereas receivers and monitors in tractors for auto-steer, among other technologies can cost more than $10,000. The benefits drones provide with their ability to survey and monitor crop conditions at a low cost are desirable for agricultural producers.

2.6. Variable Rate Nitrogen Application

Using traditional farming methods, nitrogen is applied at a uniform rate during different times of the growing season (Roberson, 2009). Variable rate technology (VRT) allows producers to apply nitrogen at fluctuating rates throughout the field. By applying nitrogen at a uniform rate, some areas of a field may receive the perfect amount of nitrogen to maximize yield potential of the crop, whereas some areas will likely be over-fertilized and others will be under-fertilized. Furthermore, nitrogen applications are often site-sensitive and weather sensitive due to varying weather conditions between planting and harvest (Roberson, 2009). Crops are only able to utilize a certain amount of nitrogen, and overapplication is costly. Additional nitrogen will often runoff to groundwater, streams, and lakes or denitrify into atmospheric greenhouse gasses (Roberson, 2009). Crop development in a field over time is an important factor to determining the optimal nitrogen rates. By using variable rate nitrogen application (VRNA), more nitrogen may be applied to areas in a field where plants will need nitrogen and less in areas of slow growth and lower nitrogen use efficiency (Roberson, 2009). Applying nitrogen at a varying rate has many benefits over traditional farming methods, such as decreased environmental impact, decreased input costs, and increased yields.

2.7. Variable Rate Seeding

Similar to variable rate nitrogen application, variable rate seeding (VRS) allows producers to vary seed density within a field. Variable rate seeding can potentially reduce input cost of seed, improve yields, and increase a producer's profit (Robinson, 2012). Seeding density is contingent on field conditions. Therefore, variable rate seeding may not fit every farm or every field. Variable rate seeding's benefit depends on the amount of variability within fields (Robinson, 2012). A uniform planting rate is the best application method in fields with uniform conditions. Variable field conditions include drainage, fertility, soil type, topography, productivity, moisture, depth, weeds, insects, leveling, and ditching (Robinson, 2012). Variable rate seeding exhibits the most benefit when variability exists in soil type, moisture, depth, leveling, ditching, and productivity (Robinson, 2012). Producers implementing variable rate seeding may receive economic benefits that result in increased profitability of the operation.

2.8. Conclusion

Although the technologies described in this chapter offer many potential benefits, most create additional costs. Many of these technologies have existed for several years and are continually improving and becoming more precise. As these technologies mature and advance, they generally decrease in cost. Many more producers may begin to utilize the technologies as they fit better with farms' budgets and goals.

CHAPTER 3. LITERATURE REVIEW

This chapter covers the seven PATs discussed in the previous chapter as well as the practice of no-till and how they are impacting the U.S. agricultural industry. A precision agriculture dealership survey conducted by Purdue University in 2017 asked dealerships to report the profitability of PAT services they offer (Erickson et al., 2017). The technology for which the greatest percentage of respondents reported making a profit was variable rate technology (VRT) fertilizer application. Among surveyed retailers, 78% offered GPS with autosteer for fertilizer and chemical applications; 73% offered automatic section control (ASC); 55% offered manual GPS guidance systems; and 34% had unmanned aerial vehicles (UAV) for internal dealership purposes. The survey reported that 80% of the participating dealerships who offer VRT fertilizer application as a service are making a profit from it, 39% are profiting from VRT seeding prescriptions, 38% are profiting from GPS guidance and autosteer sales and support, 22% are profiting from satellite imagery services, and 14 % are profiting from unmanned aerial vehicle services (Erickson et al., 2017). Although dealerships' adoption of these precision agriculture technologies is likely much different than independent farmers, these statistics are useful for developing hypotheses as adoption trends may follow the same pattern.

3.1. Global Positioning System Guidance

The most widely used PAT is GPS guidance and auto-steer systems for tractors (Lowenberg-DeBoer, 2015). For corn production, using GPS-equipped vehicles to create precise field boundaries saves an estimated $15 per acre (United States Department of Agriculture, 2019b). The Purdue dealership survey found that GPS guidance with manual controls, or light bar systems, reached peak adoption in 2009 with a 79% adoption rate (Erickson et al., 2017). Since then usage has been on the decline and adoption dropped to 55% by 2017. The dealers that participated in this survey estimated that GPS guidance and auto-steer would have the highest adoption rate among PATs used by their clientele. The dealers estimated 60% producer adoption of these technologies in 2017 and expect adoption to rise to 72% by 2020 (Erickson et al., 2017). Although usage of manual GPS guidance has been declining, it appears that users are switching over to GPS guidance with automatic controls, also known as auto-steer.

3.2. Auto-Steer

Auto-steer is the newer and improved version of GPS lightbar guidance that many producers are adopting. The dealership survey showed that auto-steer's usage went from 53% to 78% from 2009 to 2017 while GPS lightbar guidance adoption usage went from 79% to 55% (Erickson et al., 2017). Previous studies on an inward drift component of only 0.5 feet for a 2,600 acre farm found sub-meter auto-steer to have a return on investment larger than the interest rate (Shockley et al., 2011). However, under these same circumstances, RTK auto-steer would not be an economically viable choice. Input savings due to reduction in overlapped area must be greater than annual auto-steer cost to be considered profitable (Shockley et al., 2011). Under different scenarios of using sub-meter, RTK, or both auto-steer systems a break-even acreage under 1,555 acres was found, with payback periods being 4.5 years or less (Shockley et al., 2011). Sub-meter auto-steer dominated RTK auto-steer for optimal production practices in the study. Other benefits of auto-steer such as reduced operator fatigue and multitasking opportunities are hard to quantify (Shockley et al., 2011).

3.3. Automatic Section Control

Like GPS guidance and auto-steer, automatic section control is also used to reduce overlapping, but in a much different way. ASC is more beneficial on irregularly shaped fields, whereas GPS guidance is more beneficial on fields that are more square in shape. The highest returns for GPS guidance alone were on square-shaped fields and the lowest returns were on irregularly-shaped fields (Smith et al., 2013). Overlap from irregularities in field shape are not reduced with GPS guidance as planter rows and sprayer nozzles do not stop on previously-covered areas of the field. GPS guidance is an effective technology when used exclusively but has proven to bring the highest returns when combined with ASC (Smith et al., 2013).

A study that analyzed the effectiveness of ASC in Tennessee found that overlapping only occurred on 13.4 acres of about 1,100 total acres across a 28-field farm. The study used a 12-row planter with 38-inch rows. If an 18 or 24-row planter would have been used instead, the number of double planted acres would have increased to 31 and 44.1 acres, respectively (Robinson, 2011). The University of Kentucky conducted a similar study using sprayers. The study concluded that a sprayer with 80-foot booms and 5-section manual controls produced an overlap of chemicals on 14.5% of the field (Luck et al., 2011). In contrast, a sprayer with 100-foot booms and 30-section automatic controls only overlapped on 2.3% of the field. These results originated from a variety of field shapes and sizes from both systems. Irregularly shaped fields and fields with inclusions like grassed waterways and woods usually have the largest savings from ASC. Overall, ASC can reduce over-application significantly, and savings typically increased with more control sections (Luck et al., 2011).

John Fulton of the Auburn University Precision Agriculture Program stated that around 70% of the self-propelled sprayers in the Midwest are using ASC (Hollis, 2011). Average savings from ASC sprayers on a countywide basis was approximately 4.5% of chemical costs. When Fulton studied Alabama growers who raise cotton, corn, soybeans or peanuts, he found that the payback period for ASC on sprayers was less than two years on farms with over 1,000 acres (Hollis, 2011). These studies indicate that ASC sprayers have direct economic benefits, which is reinforced by producers' high adoption rate.

3.4. Satellite Imagery

Satellite imagery is an older technology that has recently become more useful in agriculture due to resolution improvements. The commercial availability of high-resolution satellite sensors, such as SPOT 5, GeoEye-1, IKONOS, WorldView 2, Sentinel-2, and QuickBird, has paved the way for field mapping (Yang et al., 2013). The resolution gap between satellite and airborne imagery has been narrowed significantly because of these satellite sensors. A 2013 study found that QuickBird and airborne imagery produced nearly the same amount of yield variability, with the QuickBird trial having slightly better accuracy. High-resolution satellite imagery can be a useful data source for mapping and estimating within-field crop yield variability (Yang et al., 2013). Satellite imagery alone does not offer substantial direct economic benefits and there are no studies that show an increased profitability for users. Field maps generated from satellite imagery are typically paired with other PATs such as VRT in order to produce noticeable returns (Yang et al., 2013). Much like satellite imagery, unmanned aircraft systems (UAS) can also assist in field mapping and provides many similar benefits.

3.5. Unmanned Aircraft Systems

Unmanned aircraft systems are one of the newest and fastest growing precision agriculture technologies. Although initially developed as military devices, congress included provisions in the 2012 FAA Modernization and Reform Act (FMRA) to allow civilians access to UAS (Fultz, 2018). In 2016, the FAA authorized the operation of drones under broad restrictions and opened doors for drone businesses. Under this new rule, drones may not be operated: if over 55 pounds; above 400 feet; over 100 miles per hour; over people not involved in the flight operation; at nighttime; or beyond the visual line of sight. Drone operators are not allowed to be in a moving vehicle unless they are in a sparsely populated area as well, but waivers granted by the FAA may bypass many of these restrictions (Fultz, 2018).

As drone related legislation is developing and regulations are weakening, it is likely that drones will play an increasingly significant role in the development of commercial and industrial sectors (Flower, 2018). Chad Colby, an Illinois grain farmer and UAV specialist estimates that agricultural users could capture 60 to 65 percent of the entire UAV market (Blake, 2015). Sales revenue from UAS could reach $82 billion over the next ten years, as there are already more than 70,000 jobs in the UAV industry (Blake, 2015). By using drones and related software instead of traditional field scouting methods to determine optimal input usage, corn producers may save an estimated $12 per acre (United States Department of Agriculture, 2019b). The impact drones have on agriculture is already immense and is only projected to grow larger.

The drone manufacturer PrecisionHawk found farmers who used drone-based aerial imagery instead of taking plot-based measurements by hand collected data over twice as efficiently and 25% more accurately (Kirkpatrick, 2019). The results from drones were more standardized, repeatable, and objective. Drones sensors can vary between visual, multispectral, thermal, and hyperspectral data all in one flight. Satellites are equipped with these same sensing technologies but are put at a disadvantage as drones have a higher resolution that offers a more precise view of crops or plants (Kirkpatrick, 2019).

The 2015 Purdue University dealership survey found that 13% of the dealers who offer or are using UAVs are making a profit, about the same are breaking even, and the majority are either losing money or are unsure (Widmar and Erickson, 2015). The retailers approximated that UAV technology was used on 2% of tillable acreage in the U.S. but expected use to increase to

16% in 2018. Past surveys show that respondents typically overestimate what happens in the future, but generally capture the trend that services are moving towards. Due to strong income pressure over the last several years, adoption of technologies that fail to convey or don't have strong economic returns will likely be low (Widmar and Erickson, 2015). This study shows that although UAV usage in agriculture is continuously growing, its overall usage is still relatively low. However, once the farm economy picks back up it is predicted that UAV sales will increase.

3.6. Variable Rate Nitrogen Application

Variable rate nitrogen application (VRNA) has been around for several years but retains issues that must be solved before wider adoption occurs. The economic benefit of using VRNA is dependent on the variability factors in a field that impact crop yield (Roberts, English, and Mahajanashetti, 2000). The two variability factors are degree of spatial variability within a field and yield response variability in different management zones. A theoretical model proposed by Roberts, English, and Mahajanashetti (2000) found that economic incentives are increased for variable rate nitrogen application as prices of both the input and output increase, as the marginal physical products of low-response and high-response land types diverge, and as the cost of services decrease. By using variable rate application to apply precise and optimal amounts of raw inputs, corn farms could save up to $22 per acre and increase operating profit by 1.1% (United States Department of Agriculture, 2019b). Lowenberg-DeBoer and Erickson (2019) analyzed many published precision agriculture adoption surveys and found a widespread pattern of 20% to 30% adoption rates for VRT fertilizer. They believe this adoption pattern suggests producers are open to the idea of VRT fertilizer, but very few producers are ready to make it a standard practice (Lowenberg-DeBoer and Erickson, 2019).

3.7. Variable Rate Seeding

Along with VRNA, variable rate seeding (VRS) is also experiencing slower adoption rates. One of the most expensive input costs for farming is seed. Variable rate seeding aims to reduce seed cost while potentially increasing yield by planting more seed on heavy ground and less seed on lighter ground (Robinson, 2012). Using precision seeding to optimize planting decisions and seed placement can save up to $6.53 per acre on seed expenses (United States Department of Agriculture, 2019b). In 2013, Monsanto tested out a new program called DEKALB FieldScripts (Myroup, 2013). This program involved 150 participating farmers in Minnesota, Iowa, Illinois, and Indiana. A variable rate seeding prescription was created for the participants and then a planter control system was used for variable rate seeding. Monsanto claims there was an average yield advantage of 5 to 10 bushels per acre over non-FieldScripts planted fields (Myroup, 2013). However, these results had no data or evidence supporting the claim and could be biased as they came from a DEKALB employee. Overall, recent research on variable rate seeding is lacking, and profitability is not evident.

3.8. No-till

No-till does not fit the definition of a PAT, however it was included in this study as it is a practice that could have explanatory effects on the adoption and usage of PATs. No-till may improve the environment and impose direct economic benefits as it is a tillage system that does not disturb the soil between harvest and planting (Lankoski, Ollikainen, and Uusitalo, 2005). The only disturbance to the soil occurs as a result of the planter seeding through the crop residue (Lankoski et al., 2005). In 2004, Holland reported no-till technology was used on 36.7% of total acreage in cultivation in the United States and Canada, and 47.5% in South America. This practice provides environmental benefits, such as reduced nitrogen runoff and soil erosion

(Stonehouse, 1997). However, no-till could harm the environment through increased dissolved phosphorus runoffs, surface water leaching into groundwater, and weeds that potentially lead to increased herbicide runoff (Lankoski et al., 2005). Decreased labor and fuel consumption, as well as lower capital investment and maintenance cost are all benefits the producer may see due to no-till usage (Lankoski et al., 2005). The environmental and economic benefits outweigh the negatives in many areas, as no-till is still commonly practiced today.

CHAPTER 4. METHODOLOGY

4.1. Data

To examine precision agriculture technology adoption and usage in North Dakota, a survey was designed to collect data on producer usage and characteristics. This survey was approved by the North Dakota State University Institutional Review Board (IRB) and circulated to randomly selected North Dakota Farm Service Agency (NDFSA) clientele. A copy of the survey used in this study is shown in Appendix A. In order to maintain the anonymity of respondents, no identifying information was collected. The survey asks for farm, farmer, and household attributes; past and present usage of precision agriculture technologies; and business practices and characteristics.

A total of 5,000 surveys were mailed out to NDFSA clientele, and 455 responses were received, resulting in a 9.1% response rate. The response rate may seem low, but many recipients were likely ineligible to answer the survey. Common reasons that caused recipients to be ineligible was their lack of involvement in operations and decision making, as well as the inability to answer questions truthfully. A South Dakota study on the relationship between conservation and precision agriculture had a useable response rate of 16.5%, and the 2013 Southern Cotton Precision Farming survey had a response rate of 13.7% (Deutz and Kolady, 2018; Hollis, 2014) . Based on these other similar studies it was predicted the response rate would be around 10% and therefore it is satisfactory. Not all respondents of the survey were farmers actively involved in decision making. For example, because the surveys were sent to owners of farmland in North Dakota, some of the respondents were landlords and trustees. All the responses were recorded and put into a database in which each survey was recorded separately.

4.1.1. Description of Survey Questions

The first portion of the survey asks demographic questions to understand who the respondents are, their relationship to the farm, and size of their farm. These questions are all asked to find patterns and groups associated with precision agriculture technology (PAT) usage. Questions were asked about standard personal attributes such as age, gender, race, marital status, and highest level of education obtained. Patterns of PAT usage may be found within these specific groups. For example, respondents who are young and with a high level of education might adopt satellite imagery more frequently. Questions about what state respondents reside in most of the year, the location of their home relative to the farmstead, the zip code in which the majority of their farmland is located, and whether they are a landlord or an operator can all be used to draw conclusions about the involvement that each respondent has on the farm. Questions regarding farm size and enterprises are also asked in this section. For example, questions were asked on the amount of crop acres owned and rented, land retirement program acres owned and rented, and if the respondent grows specialty crops and or raises commercial livestock.

While acreage owned and rented shows the exact size of the farm, it is also important to understand the farms' goals and objectives. Some questions that help to define these objectives ask whether the respondent is strictly producing grains, has pasture land and raises commercial livestock, has all of their acres in a land retirement program, or has land in all three of these categories. The size of a farm and its focus could have many implications on PAT usage. Farms that contain mostly land retirement acres or only have pastureland for commercial livestock likely won't adopt many of the PATs listed in the survey. All these demographic questions may help with the understanding of who adopts PATs and why they adopt PATs.

The next section of the survey focuses on precision agriculture technology usage. The technologies in question are GPS guidance; auto-steer; ASC sprayer; satellite imagery for nitrogen management; UAS for nitrogen management; UAS for direct crop scouting; variable rate nitrogen application; variable rate seeding; as well as the practice of no-till. The survey asks respondents for their estimated current usage of each technology, whether they have never used the technology, or whether they used it in the past. To go along with the questions regarding technology usage, the survey also asks the respondents if they plan to decrease, increase, or remain at the same level of usage for each technology within the next 5 years. Some of the technologies are broken down into usage within specific crops such as corn, soybeans, wheat and other crops. This study aims to identify which specific attributes make an operator or farm more or less likely to adopt PATs.

Questions on business practices and characteristics comprise the third and final section of the survey. Respondents are asked to rank several farm goals on a scale varying from “not important” to “very important.” Computer usage questions were also asked on a scale from “not used” to “very frequently used”. Other questions asked in this section identify if anyone in the household works off-farm for pay, the household income from farming, the net worth of the farm, whether a transition plan exists, and who the primary decision maker is. All these questions can help define the objectives of the farm and what direction it is headed towards.

4.1.2. Description of Survey Data

In total, 455 survey responses were recorded, but not all respondents answered each question or answered each question in a usable manner. Therefore, the statistics reported in this section are based on the usable responses for each question, not out of the total 455. The youngest survey respondent was 29 years old and the oldest respondent was 98 years old. The median age of respondents was 63 with a standard deviation of 14.25 years. Average farmer age is 58 years old according to the USDA, so the survey respondents were slightly older than average (United States Department of Agriculture 2019c). It should also be noted that respondents are not necessarily farmers but are landowners. Of those who answered the question regarding their relationship to the farm, 49% were owners actively involved in operations; 8% were owners actively involved in decision making but not operations; 14% were owners not actively involved in operations or decision making; 22% were landlords; 2% were trustees; and 4% were other. The average survey respondent reported 31.5 years of farm decision making experience.

Males accounted for 84% of survey respondents while the other 16% were females. According to the 2012 Census of Agriculture[1] 13.67% of principal farm operators were women, which closely resembles the survey results (United States Department of Agriculture, 2012). Regarding marital status, 78% are married, 7% divorced, 9% widowed, 6% never married, and less than 1% are living with a partner. A question about the highest level of education for respondents showed that 2% did not graduate from high school, 13% got a high school diploma, 19% attended some college, 17% got an associate's degree, 28% received a bachelor's degree, 5% attended some graduate school, and 16% received a graduate or professional degree. Over half (58%) of respondents reside on the farm, 8% live in a rural area near their farm, and 34% live in a town or city near their farm.

[1] Due to a wording change in the 2017 Census of Agriculture, the 2012 Census was used instead as it was more relevant to this study. The data in the 2012 Census reflected farms with women principal operators whereas the 2017 data reflected farms with female producers. This wording change resulted in a drastic statistical difference, increasing from 13.67% to nearly 56%.

4.1.3. Variables

Survey data were compiled into variables used in this study. Age is an important variable as young producers who are decision makers are assumed to be more likely to adopt, due to having more exposure and knowledge of PATs. On the other hand, these young producers are also assumed to be more leveraged financially, which would make them less likely to adopt. Evaluating if age has a significant effect on adoption of PATs, and whether the effect is positive or negative is relevant to this study as it is used in similar studies and may support underlying research. Education level has also been analyzed in similar studies and it is generalized that with higher levels of education among farmers, the more likely they are to adopt PATs. In this study, education level was used as a dummy variable, receiving a 0 for an education level lower than an associate's degree and a 1 if an associate's degree or higher was attained. Acres in cultivation was used as it gives a more accurate representation of PAT usage than total acres. Total acres include land retirement programs, pasture land, and other idle land, which PATs are unlikely to be used on. Acres in cultivation only measures cropland: corn, soybeans, wheat, and other crops. Cropland is generally what most PATs get used for, and narrowing the focus allows for a more accurate representation for intensity of usage.

Five PATs and their current usage will be used as variables in this study to evaluate the impact they have on one another. These PAT variables were created by taking the acres they were used on divided by the total acres in cultivation. Although data on UAS for nitrogen management and UAS for direct crop scouting was collected, these variables were excluded from the analysis due to low response. GPS guidance and autosteer were combined as one variable, as many respondents answered as if they were the same technology. The PAT variables that were used for creating econometric models are GPS share, ASC share, satellite share, VRNA share, and VRS share.

There are few farms with high value specialty crops in North Dakota, and therefore acres in cultivation and net farm worth generally move in the same direction. Net worth of a farm business is an effective variable that can help to understand farm size, but due to strong covariances with acres in cultivation it was dropped from the study as it would lead to inaccurate results. Previous research indicates that different crops producers grow can have a wide impact on their farming practices and usage of PATs. Because of this, crop share variables were created and included in this study. These variables were calculated by taking the total acres for each crop divided by acres in cultivation to gain an understanding of the contribution each one has on the farm. Table 4.1 below introduces all the variables used in the model with an explanation of what they are.

Table 4.1: Description of Variables

Variable	Explanation
Age	Respondent’s age in years.
Education	Dummy variable for highest education level received. Positive for associate’s degree and above, 0 for levels below.
Acres in Cultivation	Total acres of cropland owned and rented divided by 1000.
GPS share	Total acres rented and owned that GPS guidance or auto-steer was used on divided by acres in cultivation.
ASC share	Total acres rented and owned that an ASC sprayer was used on divided by acres in cultivation.
Satellite share	Total acres rented and owned that satellite imagery was used on divided by acres in cultivation.
VRNA share	Total acres rented and owned that VRNA was used on divided by acres in cultivation.
VRS share	Total acres rented and owned that VRS was used on divided by acres in cultivation.
No-till share	Total acres rented and owned that no-till was practiced on divided by acres in cultivation.
Corn share	Total corn acres owned and rented divided by acres in cultivation.
Soybean share	Total soybean acres owned and rented divided by acres in cultivation.
Wheat share	Total wheat acres owned and rented divided by acres in cultivation.
Other crop share	Total other crop acres owned and rented divided by acres in cultivation.

The average, standard deviation, maximum, and minimum values for all the variables that were used in the regression models are presented in Table 4.2 below.

Table 4.2: Variable Statistics

	Average	Standard Deviation	Maximum	Minimum
Age	57.101	13.083	96	29
Education	0.633	0.482	1	0
Acres in Cultivation	1.797	2.324	15.9	0
GPS share	0.500	0.492	1	0
ASC share	0.407	0.479	1	0
Satellite share	0.069	0.204	1	0
VRNA share	0.133	0.274	1	0
VRS share	0.104	0.253	1	0
Corn share	0.142	0.201	1	0
Soybean share	0.249	0.245	1	0
Wheat share	0.230	0.246	1	0
Other share	0.176	0.252	1	0

It can be noted that all the share variables have a maximum of 1 and a minimum of 0. This is because they are represented in percentage terms, 1 being 100% and 0 being 0%. For example, the maximum a producer used VRNA on was 100% of their acres in cultivation. It can also be noted that education has a maximum of 1 and a minimum of 0, as it is a dummy variable.

Out of the 455 survey responses received, 237 of the respondents were owners actively involved in decision making. For the purpose of this study, this group of respondents will be referred to as decision makers. These decision makers are likely more knowledgeable about the operations and respond with more accurate and useful data. By using a segregated sample of decision makers, average farmer age drops from 63 years old to 57.1 years old, closely resembling the USDA's average farmer age of 58 (United States Department of Agriculture 2019c). The age of these decision makers has a standard deviation of 13.1 years. Average years involved in decision making was 31.7 with a standard deviation of 14.5 years, indicating these respondents had a good understanding of their farm operations. Due to these reasons, a segregated sample of decision makers was used to obtain the regression results. Averages of acreage owned and rented for specific crops, acres in cultivation, and total acres are given in Table 4.3 below for this segregated sample.

Table 4.3: Crop Acre Totals

	Average	Standard Deviation	Maximum	Non-zero Minimum
Corn Owned	121.89	222.69	1250	20
Corn Rented	143.61	321.00	2400	13
Total Corn	265.51	436.39	3000	25
Soybeans Owned	203.85	360.79	2500	15
Soybean Rented	304.39	546.34	3400	70
Total Soybean	508.24	721.69	4400	15
Wheat Owned	266.85	572.55	4800	12
Wheat Rented	357.63	813.56	7200	30
Total Wheat	624.48	1217.62	12000	15
Other Crops Owned	151.45	352.23	2750	10
Other Crops Rented	246.92	619.03	5000	20
Total Other Crops	398.37	764.52	5000	10
Total Acres Owned	1189.19	1628.35	16150	5
Total Acres Rented	1354.14	1880.42	11200	67
Total Acres	2543.33	2834.88	21150	10
Acres in Cultivation	1796.59	2323.55	15900	10

Variables of owned acres, rented acres, and total acres in Table 4.3 were made for corn, soybeans, wheat, and other crops. The total variable for each commodity is simply owned acres plus rented acres. The acres in cultivation variable has different values than total acres, because only crops are considered for acres in cultivation, excluding pasture, land retirement programs, and other idle land. The standard deviations are large due to many of the responses being zero, as many decision makers raised only one or two of the crops. The averages were calculated counting zeros but were truncated from the minimum values to get an accurate representation of how small some farms are, otherwise all minimum values were zero. Maximum values were also included to show how big some crop farms are compared to others. Table 4.3 shows that farms surveyed ranged from 10 acres in cultivation up to 15,900. Table 4.4 below shows the average of crop dummy variables, indicating the percentage of those who grow each crop along with the standard deviation.

Table 4.4: Crop Percentages

	Average	Standard deviation
Total Acres Dummy	0.92	0.27
Acres in Cultivation Dummy	0.80	0.40
Corn Dummy	0.50	0.50
Soybean Dummy	0.61	0.49
Wheat Dummy	0.59	0.49
Other Dummy	0.49	0.50

These dummy variables were given a 1 if the respondent owned or rented any land in a category, and a 0 if not. By looking at the average of the variables in Table 4.4 it can be seen that 92% of decision makers responded that they owned or rented at least 1 acre of land. The acres in cultivation average dropped down to 80%, which is the amount of respondents who raise crop(s). This table indicates there were many producers in each category, with the lowest being other crops at 49%, which was 115 respondents.

A correlation table of corn, soybean, wheat, and other crop share are shown below in Table 4.5.

Table 4.5: Crop Share Correlations

	Corn	Wheat	Soybeans	Other
Corn share	1			
Wheat share	-0.5067	1		
Soybean share	0.0693	-0.3845	1	
Other crop share	-0.39	-0.1759	-0.5922	1

As can be seen in Table 4.5, corn and soybeans have the least correlation, and wheat and other crops have the second least. Because of the correlation, models including corn share and soybean share were ran separately from models with wheat share and other crop share.

4.1.4. Hypotheses

Several predictions exist regarding the effect of variables on PAT adoption and usage. Age is expected to have negative effects on the adoption and intensity of most PATs, because older producers are less likely to have ample knowledge on how to use the technologies (Ling and Bextine, 2017). Education is predicted to have mainly positive effects, as higher education generally leads to a better understanding of how to use the technologies and therefore reduces the learning curve. As acres in cultivation increases, PAT adoption is also likely to increase as larger farms often receive greater economic benefits due to economies of scale (Tey and Brindal, 2012). Variable rate technologies are expected to increase the adoption of satellite imagery, because satellite imagery does not provide much economic benefit without being paired with VRT (Yang et al., 2013). It is predicted that corn and soybean farms will have the largest positive impact on PAT's as they have relatively high costs of production, while wheat will likely have negative effects due to its lower cost of production.

4.2. Methods

This study attempts to identify groups and patterns in the data to get a better understanding of the type of farmer that adopts PATs, as well as the impact that PATs have on each other. To accomplish these goals, a double-hurdle model is used.

The double-hurdle model is designed for dependent variables with endpoints of an interval with a positive probability that are continuously distributed over the interior of the interval (García 2013). The distribution of PATs adopted will be relatively continuous over positive values, with zero PATs adopted being the corner solution, as an individual cannot use a negative amount of PATs. There are two decisions that need to be made within a double-hurdle model. The participation decision is the first hurdle, and the quantity decision is the second hurdle (García 2013). In this study, the participation decision will be whether the individual chooses to use a PAT, and the quantity decision is how many acres the PAT gets used on relative to total acres in cultivation.

4.2.1. Theoretical Model

The double-hurdle model assumes two sequential decisions are made: the decision to adopt a technology, and the intensity of usage for the technology (Olwande, Sikei and Mathenge 2009). Different latent variables are used for modeling each decision process. The first hurdle is estimated with a probit model as a sample selection equation. This hurdle model represents the probability of a limit observation, which is expressed as:

$$d_i = 1 \text{ if } d_i^* > 0 \text{ and } 0 \text{ if } d_i^* \leq 0$$

$$d^* = z'_i \alpha + \varepsilon_i \tag{1}$$

where $d*_i$ is the latent discrete choice variable for adoption, z is hypothesized to impact adoption choice as a vector of explanatory variables, α represents a vector of parameters, and ε is used as the standard error term. This first hurdle, or probit model, includes all responses (Olwande et al. 2009).

An outcome equation is involved in the second hurdle that uses a truncated model to determine the intensity at which the technology gets used (Olwande et al. 2009). Only positive valued responses regarding PAT usage are considered in the second hurdle, meaning that respondents that do not use a PAT are ignored in this equation. This truncated model is given by:

$$y_i = y_i^* \text{ if } y_i^* > 0 \text{ and } d_i^* > 0$$

$$y_i = 0 \text{ otherwise}$$

$$y^* = x'_i\beta + u_i \tag{2}$$

where y_i is the intensity of adoption for the technology, x is hypothesized to influence intensity of technology use as a vector of explanatory variables, β is a vector of parameters, and u is the standard error term (Olwande et al. 2009).

The decision to adopt a technology or not and its intensity of use can be jointly modeled if the decisions are made simultaneously by the consumer (Martínez-Espiñeira 2006). The decisions can be modeled independently if they are made separately, or if one decision is made first that affects the other one, as in the dominance model, the decisions can be modelled sequentially (Martínez-Espiñeira 2006). If the decisions are made separately the independence model will be applied, and the error terms can be defined as:

$$\varepsilon_i \sim N(0,1)$$

$$u_i \sim N(0,\delta^2) \tag{3}$$

If the two decisions are jointly made the dependent double-hurdle model applies, the error terms are given by:

$$(\varepsilon_i u_i) \sim BVN(0, Y)$$

$$\text{where } Y = \begin{bmatrix} 1 & \rho\delta \\ \rho\delta & \delta^2 \end{bmatrix} \tag{4}$$

If there is a relationship with the adoption decision and the intensity of adoption, it is said to be a dependent model (Olwande et al. 2009). This dependent model is expressed as:

$$\rho = \frac{cov(\varepsilon_i u_i)}{\sqrt{var(\varepsilon_i) var(u_i)}} \tag{5}$$

There is dominance if $\rho = 0$, because the zeros are not standard corner solutions and are only associated to non-adopters. This causes the model to decompose into a standard ordinary least squares for *y* and probit for adoption (Olwande et al. 2009).

The error terms ε_i and u_i are assumed to be independently and normally distributed. In a double-hurdle model the observed variable is:

$$y_i = d_i y_i^* \tag{6}$$

For the double-hurdle model the log-likelihood function is:

$$LogL = \sum_0 ln\left[1 - \emptyset(z'_i\alpha)\emptyset\left(\frac{x'_i\beta}{\delta}\right)\right] + \sum ln\left[\emptyset(z'_i\alpha)\frac{1}{\delta}\emptyset\left(\frac{y_i - x'_i\beta}{\delta}\right)\right] \tag{7}$$

Previous studies found that the double-hurdle model yields better empirical results than the Tobit model (Moffatt, 2005; Martínez-Espiñeira, 2006). Therefore, the decision to adopt PA technologies and the intensity of use for the technologies will be estimated using a double-hurdle model.

4.2.2. Empirical Model

A series of different variables were used to understand the adoption and intensity of usage for different PATs including: age, education, acres in cultivation, GPS share, ASC share, satellite share, VRNA share, VRS share, corn share, soybean share, wheat share, and other crop share. The explanation of these independent variables can be seen in Table 4.1. The five PAT variables (GPS share, ASC share, Satellite share, VRNA share, and VRS share) were used as dependent variables in individual double hurdle models.

Two separate stochastic processes are used in the double hurdle model to determine the decision to use precision agriculture technology and the intensity of the technology's usage (Cragg 1971). The double hurdle model does not put a restriction on the explanatory variables, which is important because an explanatory variable could have a different effect in the two stages. This method allows us to estimate whether a farmer chooses to use a PAT first, and then what factors affect the intensity of PAT usage. In the first hurdle, the maximum likelihood estimator (MLE) can be obtained from a probit estimator. The MLE is estimated from a truncated normal regression in the second hurdle. A probit model is used to represent the first hurdle model (Cragg 1971):

$$AdoptPATech^{*} = X_{it}\gamma + \varepsilon_{it}, \;\; if \;\; AdoptPATech = 1[AdoptPATech^{*} > 0]$$

$$AdoptPATech^{*} = 0, \;\; if \;\; AdoptPATech = 0[AdoptPATech^{*} = 0] \tag{8}$$

where *AdoptPATech*=1 if the farmer adopts a precision agriculture technology, and *AdoptPATech*=0 if the farmer does not adopt. X_{it} are factors affecting the decision to adopt a precision agriculture technology and ε_{it} is the error term.

In the second hurdle the dependent variable is the number of acres the PAT is used on divided by total acreage in cultivation. Acres in cultivation was used rather than total acres to get a more accurate measure of intensity of use, as land retirement programs, pasture land, and idle land do not have much need for PATs. A truncated normal regression is used to represent the second hurdle of the model (Cragg, 1971):

$$\frac{PATacres}{AcresInCultivation} = Z_{it}\beta + u_{it} \tag{9}$$

where *PATacres/AcresInCultivation* is the intensity of precision agriculture technology usage, Z_{it} are factors affecting the decision to adopt PAT and u_{it} is the error term. The error terms between hurdle 1 and hurdle 2 are assumed to be independent and normally distributed and have a covariance between the two errors equal to zero.

CHAPTER 5. RESULTS

5.1. Results and Discussion of Adoption Models

A double-hurdle model was used to examine what factors affect the adoption and usage of PATs for North Dakota producers. The double-hurdle model provides individual estimates for the adoption and intensity of PAT usage. Education was found to have insignificant effects in all adoption models, so it was omitted as it did not change the sign and significance of any other variables. Also, as mentioned in Chapter 4, corn and soybeans were not used in the same models as wheat and other crops, due to multicollinearity. One set of crops was included in the adoption model and the other was included in the intensity model in the order that maximized the pseudo R-squared for each PAT model. This was done to avoid multicollinearity, yet still allowed results for each crop variable. Results for the PAT adoption models can be seen in Table 5.1.

Table 5.1: Empirical Results for the PAT Adoption Models

Independent Variable	Dependent Variables (Technology Adopted) (1) VRS	(2) VRNA	(3) Satellite	(4) GPS	(5) ASC
Age	-0.003	-0.005	-0.022**	-0.017**	-0.016*
	(0.009)	(0.008)	(0.010)	(0.008)	(0.009)
Acres in Cultivation	0.240***	0.246***	0.113**	0.449***	0.476***
	(0.055)	(0.053)	(0.055)	(0.086)	(0.090)
No-till share	0.618**	0.300	-0.760**	0.332	0.683***
	(0.252)	(0.238)	(0.333)	(0.235)	(0.254)
GPS share	0.063	0.325*			0.223
	(0.234)	(0.178)			(0.163)
VRNA share			1.937***		0.643
			(0.356)		(0.392)
Corn share				1.408***	1.939***
				(0.516)	(0.588)
Soybean share				0.159	1.008**
				(0.459)	(0.505)
Wheat share	-2.645***	-2.475***	0.207		
	(0.606)	(0.575)	(0.685)		
Other crop share	-1.045**	-0.572	0.516		
	(0.480)	(0.435)	(0.560)		
Constant	-0.426	-0.277	-0.496	0.095	-1.092*
	(0.570)	(0.527)	(0.599)	(0.611)	(0.645)
Observations	189	189	189	189	189

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

LR chi2	62.01	59.55	63.34	71.91	127.59
Prob > chi2	0	0	0	0	0
Log likelihood	-94.13	-109.47	-58.06	-173.60	-103.37
Pseudo R_2	0.2478	0.2138	0.353	0.1716	0.3816

A negative coefficient is attached to age in all the models in Table 5.1, but it is only significant for the adoption of satellite imagery, GPS, and ASC sprayer. It is significant at a 5% level for satellite imagery and GPS, and at a 10% level for ASC. Age was hypothesized to negatively affect the adoption of PATs, which is validated by the model. This relationship is likely due to older producers having less knowledge and exposure to these technologies (Ling and Bextine, 2017).

Acres in cultivation had a positive significant effect on the adoption of all PATs. Acres in cultivation was significant at a 5% level for satellite imagery and a 1% level for the four others. As acreage increases, field variability often does as well, making VRS and VRNA more appealing to producers due to the potential for greater input savings. The positive effect that acres in cultivation had on satellite imagery is likely due to reduced crop scouting, as well satellite imagery's compatibility with the VRTs these large farms have adopted. GPS and ASC both provide cost savings by reducing overlap (Luck et al., 2011; Schimmelpfennig, 2016; Smith et al., 2013). The larger a farm is, the more beneficial ASC and GPS become due to increased direct economic benefits.

No-till share had a positive significant effect on both ASC and VRS but had a negatively significant effect on satellite imagery. The positive effect no-till had on ASC was significant at the 1% level. It is possible that on no-till ground it is harder to judge when to shut off spray booms around headlands, sloughs, or other obstacles in a field because of stubble. Therefore, the adoption of an ASC sprayer on no-till ground will provide increased savings from reduced overlap. No-till's positive effect on VRS adoption was significant at the 5% level. Similar to ASC, VRS incorporates row shut-off which also helps to reduce overlap and provides cost savings but on seed (Robinson, 2012). The probable reason for no-till's positive effect on VRS adoption is also likely due to shut-off points being harder for operators to judge on no-till ground. No-till had a negatively significant effect on satellite imagery adoption at the 5% level, likely because variable rate prescriptions are harder to create on no-till ground. The NDVI measures that satellite imagery uses for early-season crop monitoring have been more precisely calibrated with exposed soil, which represents fields that use conventional tillage (Milas and Vincent, 2017). The early season of crop growth is a critical time to manage field variability and with no-till practices crop stubble often gets in the way when attempting to recognize variation with satellite imagery.

GPS has a positive effect on the adoption of VRNA, with a significance at the 10% level. VRNA adoption is preconditioned on GPS, as VRTs cannot be used without it. Not only is GPS required to use VRNA, but prior adoption marginalizes the cost of adopting VRNA. However, it was surprising that GPS was not significant in the VRS or ASC adoption models even though it is also a precondition for those technologies.

The relationship between VRNA and satellite imagery adoption was positive and significant at a 1% level. This confirms the hypothesis that VRTs have positive effects on satellite imagery use, likely because satellite imagery can provide variable rate prescriptions and does not offer substantial economic benefit without VRT (Yang et al., 2013).

Due to multicollinearity, corn and soybean shares were included in the GPS and ASC adoption models, whereas wheat and other crops were included in the VRS, VRNA, and satellite imagery models. The corn share was positive and significant at the 1% level in the GPS and ASC models. Corn is a relatively high input crop, and the savings that both GPS and ASC create by reducing overlap likely outweighs the costs even for mid-sized corn farms. Literature suggested that these two technologies provided the largest direct economic savings (Hollis, 2011; Shockley et al., 2011). The positive impact on the adoption of GPS and ASC sprayers is potentially because corn inputs are more expensive than other crops. Similarly, soybeans have relatively high input costs, specifically for chemicals. In North Dakota, typical soybean practices include a pre-emergent spray and two post emergent applications of herbicides mixed with other chemicals, such as insecticides. The soybean share is significant at the 5% level for ASC sprayer adoption, which is likely due to large potential savings on chemicals.

At the 1% significance level, wheat share had negative effects on the adoption of VRS and VRNA. Wheat's negative impact on VRS adoption is likely because wheat seed size is small, and it is generally solid seeded. Solid seeding application is generally performed with an air seeder or by a floater. Adopting VRS on an air seeder would likely be more costly than on planters with widely spaced row units. Row units on air seeders are typically spaced 5-10 inches apart, whereas row units on corn planters are often spaced 20-30 inches apart. These additional row units would increase the initial investment cost of VRS, which is likely the cause of this negative effect. The wheat share's negative impact on VRNA is probably because nitrogen is typically applied at a low rate on wheat and in-season application is not often required.

Other crop share had a negative effect on VRS adoption. Small seed size and solid seeding application is common for most other crops raised in North Dakota such as barley, canola, oats, rye, flax, and durum, which is likely the reason for the negative effect on VRS. Because the survey respondents were not asked to specify the other crops that were raised, it is difficult to thoroughly explain this variable's effects.

The pseudo R-squared measures listed in Table 5.1 indicate that 24.8% of the adoption of VRS and 21.4% of the adoption of VRNA is explained by the variables used in their models. Satellite imagery and ASC had the highest pseudo R-squared measures of 34.3% and 38.2%, respectively. These results were satisfactory and show the variables used in the model are useful in explaining the adoption of these technologies. GPS share had the lowest pseudo R-squared measures at 17.2%. This makes sense, as GPS is a precondition for many of the other technologies in this study leading to few independent variables in its model.

For additional details on these adoption models, please refer to the marginal effects tables in Appendix B. Marginal effects help explain the impact that independent variables have on the adoption of PATs, while holding everything else constant. In the adoption models, the quantities of interest are the marginal effects of changes in the independent variable on the conditional response probability (Angrist, 2001). The coefficients in the adoption models provide insight on the sign and significance, but not on the absolute magnitude of these effects (Fernández-Va 2009). The marginal effects are calculated as a one-unit increase of the independent variable on the conditional probability (Fernández-Va, 2009).

5.2. Results and Discussion of Intensity Models

The intensity models can be seen in Table 5.2 below. Because this is the second hurdle, only adopters' effects are displayed in these models. The results should be interpreted as if a producer has already adopted the PAT in question. Unlike the adoption models, these intensity models do not require a marginal effects model for interpretation of the coefficients.

Table 5.2: Empirical Results for the PAT Intensity Models

	Dependent Variables (Share of Acreage for Technology)				
INDEPENDENT VARIABLES	(1) VRS	(2) VRNA	(3) Satellite	(4) GPS	(5) ASC
Age					-0.005**
					(0.002)
Education	-0.324	0.316	-0.174	-0.126	
	(0.228)	(0.243)	(0.142)	(0.113)	
Acres in Cultivation	-0.139**	-0.063	0.029	-0.019	-0.016
	(0.069)	(0.048)	(0.024)	(0.021)	(0.012)
No-till share	0.238	0.451*	0.280*	0.049	0.129**
	(0.240)	(0.235)	(0.143)	(0.109)	(0.065)
GPS share	-0.127	0.027			0.135*
	(0.253)	(0.235)			(0.079)
ASC share					
VRNA share			0.244		0.171**
			(0.190)		(0.083)
Corn share	0.615	0.518	0.511		
	(0.601)	(0.476)	(0.444)		
Soybean share	0.657	-0.237	-0.315		
	(0.653)	(0.577)	(0.394)		
Wheat share				0.507**	0.322**
				(0.239)	(0.158)
Other crop share				-0.179	-0.619***
				(0.288)	(0.184)
Constant	0.478	-0.076	0.275	1.015***	1.110***
	(0.458)	(0.485)	(0.196)	(0.129)	(0.165)
Observations	50	65	32	122	103

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Age and education were chosen in each model depending on which had the most explanatory power, and although education was not statistically significant in any intensity models it produced a higher pseudo r-squared value than age in models 1 through 4. Regardless if age or education was used in the intensity models, all other coefficient's retained the same sign and significance. Age was used in the ASC intensity model and had a negative effect that is significant at the 5% level. This is indicating that if ASC has been adopted, older producers will use it less intensely. Age's significance illustrates that a one-year increase in age decreases the proportion of acreage that an ASC sprayer gets used on by 0.5%. One possible reason for this is that as producers get older, they reduce the amount of acreage they farm. It is not probable that older producers would revert to using section control with manual controls after learning to use the technology. This shows that age and education do not have much effect on the intensity of which PATs are used, which was unexpected and contradicted the hypothesis.

Increasing acres in cultivation by 1,000 acres decreases the proportion of acres VRS is used on by 13.9%. A possible explanation for this is that these larger farms have more than one planter and adopt one with VRS to use on fields with the most variability and have another planter without VRS that they use on fields with the least variability.

No-till share had a positive significant effect on VRNA, satellite imagery, and ASC in the intensity models. No-till was significant at a 10% level in the VRNA and satellite models, and a 5% level in the ASC model. A reason for VRNA's increased intensity of use could be because nitrogen cannot be applied through tillage. Therefore, a sprayer or fertilizer spreader must be used to apply nitrogen. A possible reason that no-till increases the intensity at which satellite imagery is used could simply be due to satellite imagery's cost on additional land being marginalized as many providers charge a subscription fee. The positive effect no-till has on the proportion of acres ASC is used on is likely because savings are increased on no-till ground compared to ground with conventional tillage. For example, if a producer practiced both no-till and conventional tillage and had two sprayers, one with ASC and one without, the ASC sprayer should be used on the no-till ground as overlapped acres would be reduced, in turn providing higher savings.

GPS was only significant in the ASC model and at the 10% level. One explanation for this significance is that ASC is preconditioned on the adoption of GPS (Smith et al., 2013). Another reason to explain why GPS increases the intensity of ASC usage could be that if a farmer has GPS and is familiar with the technology, they will be more comfortable using ASC on a large portion of their acreage soon after adoption.

VRNA share was positive and significant at the 5% level for ASC intensity of use. The coefficient value for VRNA in the ASC intensity model signifies that if a producer has already adopted an ASC sprayer, and goes from not using VRNA to 100% usage, the producer is predicted to increase the proportion of land he uses ASC on by 17.1%. ASC and VRNA share many of the same components to be adopted, so it is possible that the positive effect could be a result of the adopter being more comfortable using the technology as they are already familiar with a similar technology

The wheat share had positive effects and was significant at the 5% level for the intensity of GPS and ASC usage. Indicating that if a producer has adopted GPS or ASC, increasing their wheat share will increase the proportion of acreage the technology is used on. Unlike row crops, wheat is generally solid seeded and when fields are sprayed crops are damaged from wheel tracks. One explanation for this positive effect could be that ASC and GPS help to reduce both overlap and the number of passes made through a field, providing increased savings on wheat fields by reducing crop damage.

Acres in cultivation had a positive significant effect on the adoption of VRS, but a negative significant effect on the proportion of acreage that VRS is used on. Probable reasons for these contrasting effects were explained earlier; larger farms likely have more field variability leading to higher savings but adopt VRS on a second planter causing intensity of use to decrease.

The only other significant contrasting effect was no-till's impact on satellite imagery in the adoption and intensity models. No-till had a negative effect on the adoption of satellite imagery, but a positive effect on the proportion of acreage satellite imagery is used on. This is likely due to satellite imagery being calibrated more precisely for conventional tillage and initial subscription costs cause many producers to use it on all or most of their land. Few variables had opposite effects between the models, and the ones that did had a logical reason as of why, indicating that the results were accurate and useful.

CHAPTER 6. CONCLUSION

6.1. Summary

Several double-hurdle models were created to analyze what impacts the adoption and intensity of usage for different precision agriculture technologies in North Dakota. Data for this study was collected by surveying producers associated with the NDFSA regarding demographics, use of precision agriculture technologies, and business characteristics. The first part of the models analyzed what impacted the adoption of precision agriculture technologies and the second part analyzed what impacted the intensity of which the technologies were used.

The adoption models proved that age had a negative effect on the adoption of satellite imagery, GPS guidance, and ASC sprayers. Acres in cultivation had a positive impact on satellite imagery, GPS guidance, and ASC, as well as VRS and VRNA, signifying that larger farms are more likely to adopt PATs. No-till had positive impacts on the adoption of VRS and ASC, signifying that overlap is more common on no-till ground as stubble makes shutoff points harder to judge, leading to increased savings when used on no-till ground. No-till also had a negative effect on the adoption of satellite imagery, signifying that satellite imagery does not work as well on no-till ground as it does on conventional tillage ground. VRNA had a positive impact on the adoption of satellite imagery, likely due to satellite imagery's ability to create VRNA prescriptions. These technologies show signs of complementary effects and likely provide greater economic benefit when used together. Both wheat and other crop share had a negative effect on the adoption of VRS, likely because they are generally solid seeded and having additional row units on planting equipment increases the initial cost of VRS adoption.

The intensity models showed that age and education do not have much influence on the intensity of PAT usage. Acres in cultivation decreases the proportion of acreage that VRS is used on. One reason for this is that large farms presumably only use VRS on their fields with the most variability. No-till had a significant positive impact on the intensity of which ASC is used, possibly because ASC reduces a greater amount of overlap on no-till ground and provides higher cost savings. The wheat and other crop share had a positive impact on ASC intensity of use, because ASC provides reduced crop damage from wheel tracks as these crops are often solid seeded.

These models revealed that there are several PATs that complement one another on adoption and intensity of use. However, other factors such age, acres in cultivation, and crop share variables were found to have negative effects on the adoption and usage of several technologies.

Overall, the results of this study show which precision agriculture technologies complement each other, as well as which crops they are most beneficial on. Due to the acres in cultivation variable having positive significance for all technologies, it is evident that larger farms are more likely to use PATs as they provide benefits from economy of scale. The results also displayed strong evidence that older producers are less inclined to adopt PATs. Further research regarding adoption, usage, and economic impact of these PATs is needed to understand if using these technologies truly benefits producers.

6.2. Further Research

Although the study produces many significant and useful results, several limitations were observed exposing areas for improvement. UAS for nitrogen management and UAS for directed crop scouting were intended to be analyzed in this study but were unfortunately omitted due to low response rates. The sample size in this study was satisfactory, so rather than increasing it in order to obtain sufficient data on UAS, a segregated sample is suggested. Circulating a questionnaire to known PAT or UAS users would be an effective way to collect this data. If a segregated sample of PAT or UAS adopters was used, a double hurdle model would no longer be useful, as one of its main purpose is to measure adoption effects, and therefore using a sample of adopters would create bias. Although a double hurdle model would no longer be useful, the goal of identifying patterns of PAT usage and the effects they have on each other would still apply and could be found using other econometric models. Another potential solution would be to conduct a similar study in a few years when UAS technology gains more exposure in the agriculture industry.

Another possible area for further research could be to expand the sample past North Dakota to surrounding states, the Midwest, or even the entire United States. This could help to gain a more widespread understanding of how these technologies are used, their impact on the agriculture sector, and how geographical areas affect adoption and use. Expanding the sample size across a wider region could also potentially solve the problem of insufficient UAS data. Furthermore, including yield monitors and soil sampling as technologies in the survey could help provide additional insight to VRT adoption and usage.

Another way to expand the research of this study could be to collect data on the cost of the technologies, and whether producers have received gains or losses from usage. The results from this study show what leads to adoption and usage of PATs but fails to quantify the profitability that these technologies generate. It would be of interest to know which technologies provide the highest gains and losses in order to help crop producers make informed investment decisions.

Overall this study has provided valuable information to help further understand PAT adoption and intensity of usage. However, expanding research beyond North Dakota and collecting data to include other relevant factors such as economic impacts, UAS, and yield monitors would help generate a better understanding on the impact PATs have on the agriculture sector.

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APPENDIX A. PRECISION AGRICULTURE ADOPTION AND USAGE SURVEY

Farm, farmer, and household attributes

1. Which US zip code contains the largest percentage of your farmland? _______________

2. Which best describes your relationship to the farm or ranch? (More than one may apply.)
   - o Owner, actively involved in operations
   - o Owner, actively involved in decision making but not in operations
   - o Owner, not actively involved in decision making or operations
   - o Landlord
   - o Trustee
   - o Other (please specify ____)

3. What is your age (in years)? __________

4. How many years have you been involved in farm operations and/or decision making? _____

5. What is your gender?
   - o Male
   - o Female
   - o Other/prefer not to say

6. What best describes your race?
   - o White
   - o Black or African-American
   - o Native American or Alaskan Native
   - o Asian
   - o Native Hawaiian or Pacific Islander
   - o Other

7. What is your marital status?
   - o Married
   - o Divorced
   - o Widowed
   - o Separated
   - o Living with partner
   - o Never married

8. How many children under 18 years old live in your household currently? __________

9. In which state do you reside the majority of the year? ________________________________

10. What is the highest level of education you have received? (Choose the applicable option furthest down the list.)
    - o Did not graduate from high school
    - o High school diploma or equivalent
    - o Attended some college
    - o Associate's degree

- Bachelor’s degree
- Some graduate or professional school
- Graduate or professional degree

11. Which best describes where you live most of the year?
- On farm
- Rural area near farm
- Town or city near farm

12. Please estimate the number of owned and rented acres in each land use. If you are a renter-operator, include all of the acres you farm (rented and owned). If you do not actively farm, include only your land.

Land use	**Acres owned**	**Acres rented**
Crops:		
Corn	________	________
Soybeans	________	________
Wheat	________	________
Other crops	________	________
Pasture (grazed or hayed)	________	________
Pasture (idle)	________	________
Land retirement programs:		
Conservation Reserve Program	________	________
Other programs	________	________
Other idle land (e.g., woodlands, wetlands, ditches, homestead)	________	________
Total acres	________	________

13. Have you grown *any* specialty, value-added, or identity-preserved crops in recent years (*examples*: Enogen® corn, organic crops, culinary herbs, certified gluten-free oats, etc.)?
- Yes
- No

14. Do you raise commercial livestock?
- Yes
- No

Past and present usage of precision agriculture technologies

1. Please indicate whether you have never used, formerly used, or currently use each of the following agricultural management practices or technologies. Also, please indicate whether you plan to alter your usage (acreage) during the next five years.

	(Only complete one of these columns per row.)			*(Only select one of these columns per row.)*		
Technology or practice	**Never used**	**Used in past**	**Estimated Current usage (acres)**	**In next 5 years, my usage (acreage) will be…**		
Unmanned aerial systems (UAS/drones) imagery for nitrogen management…				**increased**	**the same**	**decreased**
… for corn	☐	☐	______	☐	☐	☐
… for wheat	☐	☐	______	☐	☐	☐
… for other crops	☐	☐	______	☐	☐	☐
Satellite imagery for nitrogen management…				**increased**	**the same**	**decreased**
… for corn	☐	☐	______	☐	☐	☐
… for wheat	☐	☐	______	☐	☐	☐
… for other crops	☐	☐	______	☐	☐	☐
No-till…				**increased**	**the same**	**decreased**
… for corn	☐	☐	______	☐	☐	☐
… for soybeans	☐	☐	______	☐	☐	☐
… for wheat	☐	☐	______	☐	☐	☐
… for other crops	☐	☐	______	☐	☐	☐
Variable rate nitrogen application…				**increased**	**the same**	**decreased**
… for corn	☐	☐	______	☐	☐	☐
… for soybeans	☐	☐	______	☐	☐	☐
… for wheat	☐	☐	______	☐	☐	☐
… for other crops	☐	☐	______	☐	☐	☐
Variable rate seeding…				**increased**	**the same**	**decreased**
… for corn	☐	☐	______	☐	☐	☐
… for soybeans	☐	☐	______	☐	☐	☐
… for wheat	☐	☐	______	☐	☐	☐
… for other crops	☐	☐	______	☐	☐	☐

Technology or practice	*(Only complete one of these columns per row.)* Never used	Used in past	Estimated Current usage (acres)	*(Only complete one of these columns per row.)* In next 5 years, my usage (acreage) will be…		
Automatic section (or row) control sprayer…				**increased**	**the same**	**decreased**
… for corn	☐	☐	______	☐	☐	☐
… for soybeans	☐	☐	______	☐	☐	☐
… for wheat	☐	☐	______	☐	☐	☐
… for other crops	☐	☐	______	☐	☐	☐
GPS guidance	☐	☐	______	☐	☐	☐
Auto-steer	☐	☐	______	☐	☐	☐
UAS-directed crop scouting	☐	☐	______	☐	☐	☐

2. Do you (or does your farm) own an unmanned aerial vehicle (or "drone") with sensors capable of collecting photographs and other imagery of your farmland?
   - ○ Yes, and I usually pilot the drone myself
   - ○ Yes, but someone else usually pilots the drone
   - ○ No, I hire someone with a drone to collect imagery for me
   - ○ No, I do not use drone-based imagery in my operation

3. On average, how much does your use of drone imagery for crop management increase your revenue for each of the following crops? (Please give your best estimate in $/acre for each crop, or mark NA if you don't use drone imagery to manage a particular crop.)
   - ○ Corn: $______ per acre ___ NA
   - ○ Wheat: $______ per acre ___ NA
   - ○ Soybean: $______ per acre ___ NA
   - ○ Other crop: $______ per acre ___ NA (Please specify crop: ___________)

4. If satellite or drone imagery is collected and used for crop management on your farm, how is the imagery processed after being collected?
   - ○ We have software on-farm that processes the image files and an agronomy service uses it as an input to make a management prescription
   - ○ We have software on-farm that processes the image files and converts the data into a management prescription (Please specify which software: __________________)
   - ○ The image files are processed off-farm and an agronomy service uses them uses them to make a management prescription

5. Do you (or does your farm) own a planter equipped with automatic section (or row) control?
   - ○ Yes
   - ○ No, but I hire someone who uses this technology for some of my acreage
   - ○ No, automatic section control is not used for planting on my farm

6. On average, by what percent has using an automatic section (or row) control planter reduced your seed cost?
   - ○ ______ percent
   - ○ I don't use this technology.

7. Do you (or does your farm) own a sprayer equipped with automatic section (or row) control?
   - ○ Yes
   - ○ No, but I hire someone to use this technology for some acreage
   - ○ No. I don't use automatic section control for spraying

8. On average, by what percent has using an automatic section (or row) control sprayer reduced your chemical cost?
   - ○ ______ percent
   - ○ I don't use this technology.

Business practices and characteristics

1. Do you or any members of your household work off-farm for pay?
   - ○ Yes
   - ○ No

2. What was your approximate total household income in 2017 from all sources (i.e., the pre-tax total combined income earned by all members of your household)?
   - ○ Under $10,000
   - ○ $10,000-$19,999
   - ○ $20,000-$29,999
   - ○ $30,000-$39,999
   - ○ $40,000-$49,999
   - ○ $50,000-$74,999
   - ○ $75,000-$99,999
   - ○ $100,000-$149,999
   - ○ $150,000-$199,999
   - ○ $200,000-$299,999
   - ○ $300,000-$399,999
   - ○ $400,000-$499,999
   - ○ $500,000 or more
   - ○ Do not wish to answer

3. At the end of 2017, what was the approximate net worth for your farm business?

- ○ Under $100,000
- ○ $100,000-$199,999
- ○ $200,000-$299,999
- ○ $300,000-$399,999
- ○ $400,000-$499,999
- ○ $500,000-$749,999
- ○ $750,000-$999,999
- ○ $1,000,000-$1,499,999
- ○ $1,500,000-$1,999,999
- ○ $2,000,000-$2,999,999
- ○ $3,000,000-$3,999,999
- ○ $4,000,000-$4,999,999
- ○ $5,000,000 or more

4. How important are these goals to you farm business over the next five years?

Goal	**Not important**	**Somewhat important**	**Moderately important**	**Important**	**Very important**
Improving farm efficiency	☐	☐	☐	☐	☐
Increasing the acreage controlled by your farm	☐	☐	☐	☐	☐
Maintaining a stable income	☐	☐	☐	☐	☐
Reducing debt	☐	☐	☐	☐	☐
Transitioning the farm to the next generation	☐	☐	☐	☐	☐

5. Do you have a farm transition plan?

- ○ Yes, the farm will be transitioned to a family member
- ○ Yes, the farm will not be transitioned to a family member
- ○ No

6. If you answered "yes" to question 6, in how many years will this transition occur? _____

7. Who is/are the primary decision maker(s) on your farm?

- o I am the primary decision maker
- o I share decision making responsibility with someone else.
  (Please identify that person: □ Spouse; □ Parent(s); □ Sibling(s); □ Child(ren); □ Other.)
- o Someone else is the primary decision maker.
- o (Please identify that person: □ Spouse; □ Parent(s); □ Sibling(s); □ Child(ren); □ Other.)

8. Who is/are the primary computer user(s) in your farming operation? (Select one.)

- You
- Spouse
- Child
- Hired employee with multiple duties
- Dedicated employee or office employee
- Other person
- No one, due to lack of internet access
- We don't use the computer

9. How often is a computer used for the following tasks in your farm business?

Task	**Never**	**Rarely**	**Occasionally**	**Frequently**	**Very frequently**
Keeping financial records	☐	☐	☐	☐	☐
Keeping production records	☐	☐	☐	☐	☐
Sending or receiving e-mails	☐	☐	☐	☐	☐
Tracking commodity prices online	☐	☐	☐	☐	☐
Marketing commodities online	☐	☐	☐	☐	☐
Purchasing farm inputs online	☐	☐	☐	☐	☐
Banking or paying bills online	☐	☐	☐	☐	☐
Filing regulatory reports online	☐	☐	☐	☐	☐
Filing taxes online	☐	☐	☐	☐	☐

APPENDIX B. MARGINAL EFFECTS

Because the coefficients from the adoption models are difficult to interpret a marginal effects table was created for each dependent variable to further explain the results. First, the marginal effects for VRS are shown in Table B.1 below.

Table B.1: VRS Marginal Effects

Independent variable	dy/dx	Std. Err.	P>z	[95% Conf. Interval]	
Age	-0.001	0.002	0.689	-0.005	0.003
Acres in Cultivation	0.062	0.012	0.000	0.038	0.085
No-till share	0.159	0.062	0.011	0.037	0.280
GPS share	0.016	0.060	0.787	-0.101	0.134
Wheat share	-0.679	0.135	0.000	-0.944	-0.415
Other crop share	-0.268	0.119	0.024	-0.502	-0.035

The p-value, labeled P>z, in the marginal effects models indicates the significance of each variable. In the VRS marginal effects model above it can be seen that acres in cultivation and wheat share are significant at the 1% level. No-till and other crop share are significant at a 5% level, whereas age and GPS share are insignificant. Using the derivates, labeled dy/dx, the marginal effect each independent variable has on the dependent variable can be obtained, while holding all else constant. So, in Table B.1 increasing acres in cultivation by 1,000 is predicted to increase the likelihood of VRS adoption by 6.2%. A reason that larger farms have greater adoption of VRS is because with more acres comes more field variability, therefore increasing savings from VRS. The dependent variable, VRS, along with all share variables are in percentage form, which can easily lead to misinterpretations of the coefficients. To interpret these, the independent share variables are assumed to be changing from 0% to 100% adoption. For example, using the results in Table B.1 shows that increasing no-till usage from 0% to 100% is predicted to increase the likelihood of VRS adoption by 15.9%. Secondly, increasing wheat share from 0% to 100% is predicted to decrease the likelihood of VRS adoption by 67.9%. Lastly, increasing other crop share from 0% to 100% is predicted to decrease the likelihood of VRS adoption by 26.8%. Although going from 0% adoption to 100% adoption of a technology is not always a realistic case for individual farmers, these marginal effects still help draw conclusions of the variables' impacts on PAT adoption.

Next, VRNA's marginal effects were analyzed in Table B.2. Acres in cultivation and wheat share are significant at the 1% level, while GPS share is significant at the 10% level. The rest of the variables are insignificant at the 10% level. A 1,000 acre increase of acres in cultivation is predicted to increase the likelihood of VRNA adoption by 7.1%, which makes sense as larger farmers were expected to use more PATs. Increasing wheat share from 0% to 100% is predicted to decrease the likelihood of VRNA adoption by 71.4%. This strong negative effect may reflect that in-season nitrogen application is uncommon on wheat. Lastly, increasing GPS share from 0% to 100% is predicted to increase the likelihood of VRNA adoption by 9.4%.

Table B.2: VRNA Marginal Effects

Independent variable	dy/dx	Std. Err.	P>z	[95% Conf. Interval]	
Age	-0.001	0.002	0.535	-0.006	0.003
Acres in Cultivation	0.071	0.013	0.000	0.046	0.096
No-till share	0.087	0.068	0.201	-0.046	0.220
GPS share	0.094	0.050	0.062	-0.005	0.192
Wheat share	-0.714	0.142	0.000	-0.992	-0.437
Other crop share	-0.165	0.124	0.182	-0.407	0.077

Additionally, satellite imagery's marginal effects are examined in Table B.3. Age is significant at a 5% level, indicating that one-year increase in age is predicted to decrease the likelihood of satellite imagery adoption by 0.4%. This is in line with the hypothesis that age has a negative effect on PAT adoption. Acres in cultivation and no-till share are also significant at a

5% level. Specifically, an increase of 1,000 acres in cultivation is predicted to increase the likelihood of satellite imagery adoption by 1.9%. Additionally, increasing no-till share from 0% to 100% is predicted to decrease the likelihood of satellite imagery adoption by 13.0%. VRNA was the most significant variable in this model, at the 1% level. Satellite imagery and VRNA are believed to be complementary in nature, as the field maps satellite imagery produces can be used as prescriptions for VRNA. Increasing VRNA share from 0% to 100% is predicted to increase the likelihood of satellite imagery adoption by 33.1%. This change is fairly large and indicates that the technologies are complementary in nature.

Table B.3: Satellite Imagery Marginal Effects

Independent variable	dy/dx	Std. Err.	P>z	[95% Conf. Interval]	
Age	-0.004	0.002	0.027	-0.007	0.000
Acres in Cultivation	0.019	0.009	0.032	0.002	0.037
No-till share	-0.130	0.056	0.020	-0.239	-0.020
VRNA share	0.331	0.052	0.000	0.228	0.434
Wheat share	0.035	0.117	0.763	-0.194	0.265
Other crop share	0.088	0.096	0.356	-0.099	0.276

GPS's marginal effects were also analyzed and can be seen in table B.4 below. Acres in cultivation and corn share were significant at the 1% level for the adoption of GPS, and age was significant at the 5% level. Therefore, a one-year increase in age is predicted to decrease the likelihood of GPS adoption by 0.5%. Secondly, an increase of 1,000 acres in cultivation is predicted to increase the likelihood of GPS adoption by 12.4%. Lastly, increasing corn share from 0% to 100% is predicted to increase the likelihood of GPS adoption by 39%.

Table B.4: GPS Marginal Effects

Independent variable	dy/dx	Std. Err.	P>z	[95% Conf. Interval]	
Age	-0.005	0.002	0.039	-0.009	0.000
Acres in Cultivation	0.124	0.019	0.000	0.087	0.161
No-till share	0.092	0.064	0.152	-0.034	0.218
Corn share	0.390	0.133	0.003	0.129	0.651
Soybean share	0.044	0.127	0.729	-0.205	0.293

Lastly, ASC's marginal effects were analyzed and are shown in Table B.5 below. Acres in cultivation, no-till share, and corn share were significant at the 1% level for the adoption of ASC, while soybean share was significant at a 5% level, as well as age and VRNA at a 10% level. A one-year increase in age is predicted to decrease the likelihood of ASC adoption by 0.4%, which reinforces the hypothesis. An increase of 1,000 acres in cultivation is predicted to increase the likelihood of ASC adoption by 11.8%. This indicates ASC benefits from economies of scale. Increasing no-till share from 0% to 100% is predicted to increase the likelihood of ASC adoption by 16.9%. This is likely due to ASC providing greater cost savings on no-till ground than on conventional tillage ground as stubble makes it hard to judge shutoff points. Increasing VRNA share from 0% to 100% is predicted to increase the likelihood of ASC adoption by 15.9%. This is likely because these technologies share many of the same components for adoption and the cost of adoption could be minimized. Furthermore, increasing corn share from 0% to 100% is predicted to increase the likelihood of ASC adoption by 48.1%. Also, increasing soybean share from 0% to 100% is predicted to increase the likelihood of ASC adoption by 25%. These results indicate that ASC works well on both corn and soybeans, likely due to expensive chemical costs for these crops that increase the savings from ASC.

Table B.5: ASC Marginal Effects

Independent variable	dy/dx	Std. Err.	P>z	[95% Conf. Interval]	
Age	-0.004	0.002	0.061	-0.008	0.000
Acres in Cultivation	0.118	0.017	0.000	0.084	0.152
No-till share	0.169	0.059	0.004	0.053	0.285
VRNA share	0.159	0.095	0.094	-0.027	0.346
GPS share	0.055	0.040	0.164	-0.023	0.133
Corn share	0.481	0.133	0.000	0.219	0.742
Soybean share	0.250	0.122	0.041	0.010	0.490