Factors Influencing Adoption and Adoption Intensity of Precision Agriculture Technologies in South Dakota

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FACTORS INFLUENCING ADOPTION AND ADOPTION INTENSITY OF PRECISION AGRICULTURE TECHNOLOGIES IN SOUTH DAKOTA

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This thesis is approved as a creditable and independent investigation by a candidate for the Master of Economics degree and is acceptable for meeting the thesis requirements for this degree. Acceptance of this thesis does not imply that the conclusions reached by the candidate are necessarily the conclusions of the major department.

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This thesis is dedicated to my parents, especially my mother, who I lost while writing this paper and my beloved wife and my son for their unending support in my life.

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ABBREVIATIONS

APAT = Adoption of Precision Agriculture Technologies

ARMS = Agricultural Resources Management Survey

CSP = Conservation Stewardship Program

EQIP = Environmental Quality Incentive Program

GIS = Geographic Information System

GPS = Global Positioning System

IA = Iowa

IoT= Internet of Things

MLE = Maximum Likelihood Estimation

MN = Minnesota

ND = North Dakota

NE = Nebraska

PATs = Precision Agriculture Technologies

PTA = Precision Technologies Adoption

SD = South Dakota

US = United States

USA = United States of America

USDA = United States Department of Agriculture

VRT = Variable Rate Technology

VRTs = Variable Rate Technologies

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ABSTRACT

FACTORS INFLUENCING ADOPTION AND ADOPTION INTENSITY OF PRECISION AGRICULTURE TECHNOLOGIES IN SOUTH DAKOTA

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Precision agriculture can play an important role in preserving the environment and improving the economic conditions of agricultural producers. This thesis analyzes the determinants of adoption and adoption intensity of precision agriculture technologies in South Dakota. This analysis uses survey data collected from 199 farms distributed over 28 different counties in South Dakota, accounting for approximately 500,000 acres of tillable agricultural land, to (1) discover the factors impacting precision technology adoption; (2) compare and contrast several characteristics among adopters and non-adopters; and (3) develop probit, count, and negative binomial models to determine the significance of explanatory variables impacting precision technology adoption and adoption intensity.

T-test results of the mean age of participants, Conservation Stewardship Program (CSP) enrollment, service center access, reliance on farm dealers for information, and computer usage for accounting purposes were statistically different between adopters and non-adopters of precision agriculture technologies. Probit model results indicate that age, spousal non-farm income, and service/repair access negatively influenced the decision to adopt, while the number of cropland acres, reliance on information from farm dealers, and use of computers for accounting activities positively impacted the decision to adopt. Results from the count model suggest that age, livestock owner status, spousal non-farm

income, and service/repair access negatively influence the intensity of precision agriculture technologies adoption, while CSP enrollment, crop-land acreage, reliance on information from farm dealers, and using computers for accounting activities positively influenced the intensity of precision agriculture technologies adoption. Results of the negative binomial model indicate that only lack of access to service/repair facilities negatively affected the adoption intensity, and the adoption of different bundles of the six most popular precision technologies (auto-steer, variable rate systems, automatic section control/shut-offs, prescription field maps, yield monitors, and GPS guidance systems), while CSP enrollment, reliance on farm dealers as an information source, and using computers for accounting activities positively influenced precision technologies adoption intensity.

The results of this study may help policy makers understand how agricultural producers perceive precision agriculture technologies in general, and the degree to which these technologies may be used to enhance productivity, profitability, and environmental quality. The result also provides useful insights on key determinants of the adoption of precision agriculture technologies. The results may further help farm dealers and repair service providers as they consider marketing precision agriculture technologies to agricultural producers. Precision agriculture technologies manufacturers and sellers can use these results to identify the demand of their product and services in the future.

CHAPTER 1

INTRODUCTION

1.0 Preface and General Information

Humans have engaged in agriculture since the beginning of history. Agricultural technology has evolved over time, including the process by which plants and animals are developed, grown, cultivated, stored, preserved, transported, and marketed. Over time, the technology used in food and fiber production has changed dramatically. A contemporary example of technological change is precision agriculture, which is a specific agricultural management system that not only utilizes modern technology, but also incorporates a holistic management approach that seeks to minimize environmental and other costs. Precision agriculture has the potential to increase yields in comparison to traditional agricultural techniques, among other potential benefits. According to Schimmelpfennig and Ebel (2011), 'Efficient input use in agriculture is increasingly a priority of producers, the public, and policymakers. One way to increase efficiency in agriculture is through the adoption of precision technologies, which use information gathered during field operations, from planting to harvest, to calibrate the application of inputs and economize on fuel use.'

Precision agriculture can be defined as the use of a single aspect of modern agricultural technology or a set of technologies for managing a variety of farming activities for the purpose of improving environmental quality and advancing economic outcomes. Precision agricultural production systems rely on modern technology and have the potential to advance agricultural systems' efficiencies. This does not necessarily imply that the technology is suitable for all producers and under all agricultural conditions, but it may help some agricultural producers to take control of their production process in efforts to improve productivity and contribute to preserving resources.

The term precision agriculture encompasses a variety of technologies, aspects of which were developed over several years and continue to be refined at the current time. One is geographic information systems (GIS), which was the first precision farming tool developed between the 1960s and the 1970s for use by research institutions. The first GIS product related to precision agriculture was a system to monitor yields spatially in 1992 (Delmar, 2018). Another important precision technology consists of yield monitoring equipment, including yield mapping which was developed in the 1990s (Adamchuk, et al., 2004). A satellite-based Global Positioning System (GPS) was first developed by the U.S. Department of Defense in the 1970s (History, 2018), and John Deere's precision farming group in Moline, Iowa first introduced the GPS receiver in 1994 (Marsh, 2018). Soil testing mechanisms, another technology, have a long history and have steadily improved over time (Anderson, 1960), particularly in terms of detecting phosphorus in the soil in 1984 (Mulla and Khosla, 2015). Over time, a wide variety of PAT systems were developed, such as different types of variable rate applications of technology for fertilizers, guidance or auto-steering systems, different monitoring systems, soil electrical conductivity measurement systems, different satellite imaging techniques, different fertilizing systems, remote sensing techniques, and spatial decisions support systems.

1.1 Justification

According to Dongoski and Selck (2017), the global population is expected to increase by 40% to 9.6 billion people by 2050. As a result, food production will need to be increased by an estimated 70% from current levels to feed the drastically increasing population, even though the available agricultural land is expected to increase by only 5%. In the United States, the average farmer will need to feed more than 265 individuals by 2050 (Dongoski and Selck, 2017). Precision agriculture provides one avenue for improving the efficiency of input use and thus for increasing agricultural output, becoming a potential tool for increasing global food production. In particular, precision farming can assist crop growers in optimizing their input usage along time, location, and situation. For example, precision agriculture techniques enable the optimal use of fertilizers, pesticides, seed distribution, and the amount of water applied. Also, precision agriculture may help mitigate climate change by lowering fuel use, optimizing nitrogen and other input usage, monitoring and correcting soil health, reducing waste, improving soil structure benefits, and reducing greenhouse gas (Breitmeyer, 2015). In addition, precision agriculture tools can help optimize storage and preservation decisions by analyzing data in real-time.

Adoption of PATs alters the cost and revenue patterns of the farm, have the potential to reduce production risks, and thus affects farm profitability (Castle, et al., 2017). PATs may also provide social benefits as a result of decreased input usage and improved efficiency.

South Dakota plays an important role in US agriculture. According to the South Dakota Department of Agriculture, agriculture is a major industry in South Dakota with an economic impact of $32.5 billion every year. South Dakota has about 19 million acres of cropland. The agriculture sector contributes about one-third of all economic activities in South Dakota as a result of agricultural production and value-added industries. South Dakota is among the top-ten leading states in crop production and most of the common individual crops production ranked from 1st to 16th during the period between 2017 and 2019 (Gerlach, 2019). Agriculture employs a large number of people, exports various crops to other countries and thereby earns foreign currency. Because PATs can play a vital role in South Dakota's agricultural sector, it is important to assess which factors affect agricultural producers' adoption decisions of precision technologies.

Acquiring knowledge of economic aspects of PAT adoption trends is important to agricultural producers, researchers, consultants, and policymakers. Related, regional adoption trends or patterns are also valuable for farmer's organizations, input producers, potential precision technology buyers, and sellers. This study seeks to identify factors that influence adoption decision among agricultural producers of the six most popular PATs in South Dakota.

1.2 Statement of the Problem and Research Objectives

PATs have potential to positively impact farm profitability and improve social efficiency. The results of PATs adoption can be understood by observing the financial stability of producers and environmental quality patterns over time. Identifying factors impacting PAT adoption decision can help policymakers and producers in designing appropriate policies regarding precision agriculture. This study will identify determinants of PAT adoption decisions based on information gathered from a survey in South Dakota in 2016.

Considerable research has been done on the use of precision farming for various crops and in different regions, but with the exception of Deutz (2018), few studies have been conducted on precision agriculture practices in the combined corn and soybean production system in the Midwest. This thesis attempts to fill this gap.

The objectives of this thesis are to study the adoption of precision agriculture, with a particular focus on corn and soybean production in South Dakota. Specific goals are to:

i. Identify factors affecting farmers' decisions to adopt different types of precision agriculture technologies (PATs),

ii. Compare and contrast characteristics between adopters and non-adopters of PATs, and

iii. Apply probit, count and negative binomial models to determine the significance of the explanatory variables that influence PAT adoption.

1.3 Organization of the Thesis

This thesis contains six chapters. The following chapter includes a brief discussion on the importance of precision agriculture in the Midwest. Chapter 3 provides a literature review of the economics of PAT. Chapter 4 introduces the conceptual model, methods, data descriptions and a summary of the survey data used in the analysis on PAT adoption in Midwestern states. Chapter 5 discusses the results and Chapter 6 concludes with a description of the result, provides recommendations, discusses limitations and suggests possible directions for future study.

CHAPTER 2

2.0 IMPORTANCE OF PRECISION AGRICULTURE IN THE MIDWEST

The Midwest – the U.S. region including the states of Illinois, Indiana, Iowa, Kansas, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, South Dakota, and Wisconsin – is sometimes referred to as the 'Heartland of America,' in part because of its prominence of agriculture and large amounts of fertile land. Agricultural production in the region is not limited to food production, but also includes raw materials for the biofuel industry.

Since the Midwest is rich with natural resources and agricultural land, it is important for the national economy. The Midwest is one of the most intensive agricultural production areas in the world; the estimated total market value of crop and livestock production in 2007 was about $77 billion (Hatfield, 2012). The agricultural industry creates a derived demand for farm-related technologies such as farm equipment, trucks, and tractors. A growing food demand creates pressures to increase agricultural production, which in turn requires an increased reliance on technology.

Table 1 shows the number of planted acres of major crops in Midwestern states as a percentage of the total number of U.S. cropland acres in 2017. The Midwest contains about 63% of active cropland in the United States. Among all Midwestern states, Iowa has the largest share of U.S. cropland acres, and Michigan the smallest. Illinois, North Dakota, and Kansas have similar amounts of cropland, and South Dakota's cropland comprises over 5% of total U.S. cropland acreage.

Table 1: Acreages of major crops planted in the Midwest, 2017

States	Total Planted Acreage (1,000 acres)	Share of Total U.S. Acreage (%)
Iowa	24,511	7.68
Kansas	23,833	7.47
North Dakota	23,687	7.42
Illinois	22,850	7.15
Minnesota	19,711	6.18
Nebraska	19,686	6.17
South Dakota	17,572	5.51
Missouri	13,533	4.24
Indiana	12,170	3.81
Ohio	10,080	3.16
Wisconsin	7,758	2.43
Michigan	6,375	1.99

Source: National Agricultural Statistics Service, Parsons and Perdue (2018).

Of the total cropland in the United States, over 127 million acres are in the Midwest, of which about 75% is used for growing corn and soybeans. The remaining 25% is used for the production of a variety of other products, including alfalfa, small grains, as well as horticultural (Todey, 2017).

Table 2 represents Midwest planted corn acreage as a percentage of total corn planted acreage in the United States. Iowa has the largest amount of corn acreage in the Midwest, with about 15% of the total U.S. production, while Michigan had the smallest corn acreage, with about 2.5% planted in the United States. Illinois and Nebraska were second and third, respectively, with 12.4% and 10.6% of total U.S. corn planted acreage. South Dakota planted about 5.7 million acres, or about 6.3% of the total. Wisconsin, North

Dakota, Missouri, and Ohio each had less than 5% of the total planted corn acreage in the United States

Table 2. Total Corn and Soybean Planted area in the Midwest, in 2017

	Corn		Soybeans	
States	Total Planted Acreage (1000 acres)	Total U. S. Percentage	Total Planted Acreage (1000 acres)	Total U. S. Percentage
Illinois	11,200	12.42	10,600	11.76
Indiana	5,350	5.93	5,950	6.60
Iowa	13,300	14.75	10,000	11.09
Kansas	5,500	6.10	5,150	5.71
Michigan	2,250	2.50	2,280	2.53
Minnesota	8,050	8.93	8,150	9.04
Missouri	3,400	3.77	5,950	6.60
Nebraska	9,550	10.59	5,700	6.32
North Dakota	3,420	3.79	7,100	7.87
Ohio	3,400	3.77	5,100	5.66
South Dakota	5,700	6.32	5,650	6.27
Wisconsin	3,900	4.33	2,150	2.38

Source: National Agricultural Statistics Service, Parsons and Perdue (2018).

Table 2 also shows the soybeans planted acreage in the Midwest. Illinois, Iowa, and Minnesota planted 11.7%, 11% and 9%, respectively, that is more than 30% of the total soybeans area planted in the US in 2017. Among the Midwest states, the position of South Dakota was 8th, planting about 6.2% of total soybeans area planted in the US. Wisconsin planted about 2.15 million acres and the position was 12th among Midwest States. In total, the soybeans planted area in the Midwest holds about 80% of total soybean planted area in the US in 2017.

Perhaps somewhat surprisingly, Table 3 shows that Indiana's PAT adoption rate in corn production is the highest among Midwestern states, although Iowa is the highest corn-producing state in terms of planted acreage. Indiana is followed by Illinois which uses

PATs on more than 50% of total planted acres. South Dakota, Minnesota, and Michigan had similar rates of adoption in corn, 34.6%, 34.6% and 33.4% of corn acres, respectively. The lowest percentage of PAT adoption was in Missouri at 27.9%. All states, except Indiana and Illinois, experienced adoption rates of less than 50% of planted corn acres while the average among the Midwestern states was about 38.9%.

Table 3. Average Rate of Precision Technologies Adoption (PTA) in Corn & Soybeans fields in Midwest

State	Percentage PTA in Corn	Percentage PTA in Soybean
Illinois	50.93	36.28
Indiana	51.53	35.59
Iowa	43.25	32.30
Kansas	38.29	20.88
Michigan	33.49	28.37
Minnesota	34.63	29.85
Missouri	27.93	23.76
Nebraska	41.49	32.69
North Dakota	46.37	41.20
Ohio	37.29	23.76
South Dakota	34.66	32.51
Wisconsin	27.95	45.94

Source: ARMS Farm Financial and Crop Production Practices / Tailored Reports: Crop Production Practices (2018).

With regards to soybeans, Table 3 shows that Kansas adopted precision technology in soybeans at a rate of 20.8% of the total planted soybeans acres between 1998 and 2006. Nebraska, South Dakota and Iowa had nearly identical PAT adoption rates in soybean production of about 32.5%, although Iowa's soybean acreage exceeded that of South Dakota and Nebraska. Illinois was the highest soybean-producing state in Midwest, and on average 36.2% of total planted acres which adopt precision technologies. Within the Midwest, Wisconsin is the lowest soybean producing state, but the precision technology adoption percentage is the highest at 45.9%. North Dakota's position was second highest with an adoption rate of precision technology in soybeans at 41.2%. North Dakota was the fourth highest soybean producing state in the Midwest. Illinois and Indiana were third and fourth in adoption at soybean technologies being 36.2% and 35.5%, respectively. According to the rank of adopting precision technology on an average the position of Minnesota is eighth, but among the Midwest soybean-producing states, it ranks third.

Table 4 compares the adoption of key technologies in soybean production in South Dakota in 2006 to nearby states. Yield monitors, yield maps and GPS devices were the most widely adopted precision technologies in the Midwest in 2006.

Table 4. Different PATs adoption rates (in %) for Soybeans in 2006

Precision Technologies	SD	ND	NE	MN	IA
Precision Agriculture Used	57.5	64.2	63.3	55.9	50.2
Yield Monitor Used	50.4	48.7	57.2	48.1	48.1
Yield Map Created	18.1	18.0	27.2	23.6	27.9
GPS Device Used to Create Soil Properties Map	9.8	8.4	13.9	14.0	17.4
VRT used for Any Purpose	-	-	9.8	2.8	7.8
VRT used for Any Fertilizing	-	-	1.0	-	7.3

Source: ARMS Farm Financial and Crop Production Practices / Tailored Reports: Crop Production Practices (2018).

Table 5 compares key technologies adopted in corn in South Dakota in 2006 with those in nearby states. Yield monitors, yield maps, GPS devices for creating soil property maps, guidance or auto-steering system used and VRT used for any purpose were the most highly adopted precision technologies in corn in the Midwest in 2010.

Table 5. Different PATs adoption rate in corn in 2010

Precision Technologies	SD	ND	NE	MN	IA
Precision Agriculture Used	74.5	80.2	76.3	63.5	81.7
Yield Monitor Used	63.2	71.1	66.9	57.1	73.4
Yield Map Created	37.8	34.7	36.6	39.4	46.4

Soil properties map based on: Soil test	7.1	-	4.8	9.1	17.3
GPS Device Used to Create Soil Properties Map	23.2	14.3	15.7	24.9	33.3
VRT used for Any Purpose	19.4	17.9	22.8	24.4	19.7
VRT used for Any Fertilizing	15.3	7.9	17.3	17.4	18.6
Guidance or Auto Steering System Used	47.6	73.4	41.3	44.8	37.2

Source: ARMS Farm Financial and Crop Production Practices / Tailored Reports: Crop Production Practices (2018)

In recent times, producers in Midwestern states have faced financial pressure, in part because bankers have tightened credit standards. Also, significant reductions in crop prices due to natural disasters such as floods, and to geopolitical issues such as the U.S.-China trade war, affect the performance of agriculture in the Midwest. For example, U.S. agricultural product sales to China fell nearly 45% in value in the first quarter of 2019 to $2.1 billion compared with $3.7 billion in 2018 (Daniels, 2019). These pressures contribute to farms ceasing operations. The number of farms was 2.04 million in 2017, down 3.2% from 2012. The average net farm income was $49,291 in 2017, down 3% from 2012 (Press, 2019). Simultaneously, average farm production expenditures increased during the same period (Minchenkov and Dorn, 2016).

Food production has been increasing over time to meet the growing demand. Due to increased output pressure, the demand for technologies also increases. In addition, climate change also threatens to hamper yields, and may negatively affect crop yields so technology adoption strategies are needed to deal with this problem (Fuglie, 2018). Farm income is not only essential for the farms themselves, but also for financial institutions in the region to maintain healthy financial condition (Oppedahl, 2019). Public investment in agricultural research and development has decreased since 2009, although private research has increased. Productivity has increased because of new technologies, economies of scale, specialization, and investment in research and development (Oppedahl, 2019). Though the number of agricultural producers has decreased, total factor productivity and total agricultural output has increased (Wang, 2017). After the 1970s, the total U.S. and other high-income countries' agricultural output growth has been increasing entirely due to productivity growth. In fact, total factor productivity growth has doubled over the last 54 years (Clancy, et al., 2018). Public funding for agricultural research increased in the latter part of the 20th century, but it declined in recent years (Clancy, et al., 2018). Attracting additional public and private investment into the agricultural sector remains critical (Clancy, et al., 2016).

According to The American Farmland Trust (2018), the Midwest is under threat because of significant loss of topsoil. The organization identifies three main challenges for Midwest agriculture, including water quality, soil health and erosion, and leased land. Large amounts of fertilizer usage reduces water quality, heavy rainfall washes away the topsoil, and farmers who rent the land do not always practice proper conservation methods or are unable to afford to do so. Swan (2012) identified some of the challenges faced by North American agriculture, such as resource depletion, land management, food waste, demographic changes, and political issues. For example, groundwater usage increased over three times since the 1950s. Farmers also face challenges with topsoil erosion. Although topsoil losses decreased about 43% between 1982 to 2007, 1.73 billion tons of surface soil continue to be lost each year (Service, 2007).

Another environmental challenge for agriculture is the question of how to maintain water quality. According to the Committee on the Role of Alternative Farming Methods in Modern Production Agriculture, et al. (1989), water pollution is the most damaging and widespread environmental problem for agricultural production. It is the largest non-point source of environmental pollution (Schierow, 1985). Pesticide use can be harmful to groundwater as well. In 1988, data from 26 states showed that regular agricultural practices increase pesticides in groundwater (Williams, et al., 1988). DeSimone, et al. (2014) found that 5% of all groundwater in the U.S. was contaminated because of human sources between 1991 and 2010. Herbicide use, including about 80% conventional pesticides, contaminated about 4% of groundwater through atrazine. A related challenge is to minimize the costs of pest control. According to Pimentel (2005) pesticide use in the United States is associated with significant costs, including adverse impacts to human health ($1.1 billion), development of pesticide resistance ($1.5 billion), crop losses ($1.4 billion), losses of other beneficial species ($2.2 billion), and ground water contamination ($2.0 billion).

Adoption of precision agriculture can provide a solution to these challenges. Precision agriculture is increasingly central to improve agricultural productivity, and it has the potential to influence the entire agricultural production system. Advances in technology can increase output but also may increase costs. While output prices are determined by market conditions, profitability also depends on input costs. If costs associated with the new technology decrease over time, then PAT adoption may improve profitability.

Precision agriculture may undergo additional improvements in the future. For example, the efficiency of sensor-based harvester systems and other equipment may undergo further improvement. Analyzing different datasets with machine learning or artificial intelligence can help prevent unwanted pests and has the potential to decrease damage and waste in the agricultural sector. Hence, financial investments in specific research can help advance precision farming.

Traditional land management techniques have contributed to a reduction in the nutritional value of soil. For example, the practice of growing a limited set of crops on the same acreage can be harmful to the soil. While using fertilizers fulfills the nutrient needs, their over-use leads to nutrient leaching. Site-specific management under precision agriculture helps to manage the land more appropriately, potentially reducing fertilizer usage, and as a result improving water quality and soil health.

An additional benefit of precision agriculture is to diminish environmental pressures. For example, by limiting the amount of fertilizer applied to the soil while maintaining its utilization by crops, the technology can limit the overuse of cropland and reduce harmful impacts on the environment. PATs continue to develop and improve over time, as do advancements in science and information technology. PATs provide one way to improve the production technology and the supply of food and fiber products. Science can aid in solving production constraints faced by agricultural producers.

According to Auernhammer (2001), precision farming reduces environmental burdens and increases the flow of information. Bongiovanni and Lowenberg-Deboer (2004) showed that using variable-rate technologies (VRT) for herbicide, pesticide and fertilizer application conserves water quality, reduces inputs use, and decreases environmental damage. In addition, PA practices prevent soil erosion and preserve soil nutrients. For example, VRT enables minimizing pesticide usage when controlling pests and additional efficiency improvements may be achievable.

A higher rate of precision technology adoption can help producers economically as well as protect the natural environment. Therefore, it is important to identify the factors that impact precision adoption decisions so producers, technology suppliers and policymakers can use this study to make optimal decisions.

CHAPTER 3

LITERATURE REVIEW

3.0 Overview

This chapter reviews the research on important features associated with the economics of PAT and its adoption patterns. While the current study focuses on economic aspects of precision agriculture applied to South Dakota, economic studies of selected technologies applied elsewhere are also considered. This study emphasizes PAT with respect to corn and soybeans, as they are the most prevalent crops in South Dakota and other parts of the Corn Belt.

3.1 Precision Farming

In general, precision agriculture or precision farming denotes a system that examines the variability of soil and crops where different types of information are collected for conducting scientific assessments, including soil and crop variability within fields, and for implementation of site-specific management to ensure optimal levels of production (Paxton, et al., 2010). Various types of modern precision technologies are used and broadly include collecting, processing, and analyzing data, and also improving site-specific management over time.

By utilizing precision farming technology, agricultural producers may be able to improve their efficiency and profitability (Batte and Arnholt, 2003). By relying on information technology, precision agriculture can improve management efficiency and minimize damage to the natural environment. In doing so, the technologies have the potential to improve productivity, increase economic efficiency, and enhance farm income.

Different types of precision technologies have been developed since the introduction of the first GPS guidance system by John Deere in the early 1990s (Schmaltz, 2017). Since then, John Deere and other companies have invested significant resources in developing and improving precision technology. Attracted by its profit potential, the increased commercial interest contributed to developing various types of technology. As a result, the global precision agriculture market value exceeded $3.58 billion in 2017, and is expected to increase to about $7.30 billion by 2023 (Markets, 2018). While precision agriculture adds to input costs, it has the potential to decrease overall operating costs and improve net returns. Purchase of the technology requires up-front investments but if it improves input efficiency, the technology can reduce agricultural producers' expenditures and lead to gains in returns (Szolnoki and Nábrádi, 2014).

Further improvement in efficiency and sustainability require additional advancements in precision farming. In 2014, Lux Research found that large farms using precision technologies on more than 5,000 acres of cropland spent on average about $24.50 per acre in input costs and increased output by about $42 per acre. They predicted that within the next ten years, precision agriculture would be a fully developed industry, covering the entire production process (Rogers, 2014).

Currently, producers use several types of PATs in crop production. Among them, the most widely used technologies are yield monitors, yield maps, soil tests, soil mapping systems, variable rate technologies, auto-guidance/GPS guidance/auto-steering systems, automatic section controls/shut-offs, grid soil sampling, aerial/satellite imagery, crop tissue sampling, and prescription field maps which will be briefly reviewed here.

3.2 Yield Monitors

A yield monitor utilizes Global Positioning System (GPS) technology and an electronic device with sensor that collects, compares and contrasts production performance by using available data for a given period or over time (Grisso, et al., 2009). Yield monitors are frequently used to map yield variation within a field. The creation of a yield map involves integrating data from various sources to represent geographical differences in soil nutrients present to enable varying fertilizer applications within a field. Using yield mapping data and statistical techniques for contrasting, a yield map analytically allows for doing exploratory data analysis (Stafford, et al., 1996). Yield monitor data and high-resolution multispectral satellite images are integrated to provide information about a field's crop condition. Producers who use yield monitors may be able to reduce cost of production, increase output and efficiency, and increase profits over time. Yield monitor systems can handle a large amount of critical information such as yield and moisture data from sensors directly recorded during harvest (Group, 2018).

There are different types of yield monitors. In the United States, weight and impact yield monitors are the most prevalent, whereas nuclear and optical yield monitors are frequently used in Western Europe. Yield monitors provide information on production variations due to soil properties, management productivity, and the impact of weather or other factors. After collecting and analyzing information over several years, producers can adjust farming practices to maximize output. The most important use of yield monitors is to provide instantaneous views of yield performance. They are also used to preserve the data for future analysis and record keeping, and summarize field variation information. Data can be compared over time to help identify the most optimal crop rotation sequence (Shearer, et al., 1999). The system can also help evaluate plant varieties or specific treatments applied to test plots, and to measure the prevalence of weeds. The combination of yield monitors and differentially corrected global positioning receivers (DGPS) can generate the yield map (BISResearch, 2015).

3.2.1 Yield Maps

A yield map is another important and widely used technology in precision farming. A yield map helps understand yield variation due to external factors such as climate, water-soil relationships, chemical and physical land properties, different soil attributes, pesticide usage, other crop inputs, and soil usage history (Doerge, 2013). Technology improvements have increased the number of sensors and improved yield maps (Adamchuk, et al., 2004). Yield map data processing and interpretation systems have improved over time (Ping and Dobermann, 2005).

A yield mapping system is a combination of basic components including a grain flow sensor, grain moisture sensor, clean grain elevator speed sensor, GPS antenna, yield monitor display, header position sensor, and travel speed sensor. These components keep track of the amount harvested, grain moisture variability, grain flows and other aspects. To get smooth and usable data all components have to be used and only average maps should be considered for judgement (Institute of Agriculture and Natural Resources-CropWatch, 2018).

Yield maps allow agricultural producers to evaluate which cropland areas are most productive and help explain yield gaps. When combined with other sources of information, yield map data can help producers adjust their pest/weed control and fertilizer usage.

3.2.2 Soil Test/Grid Soil Sampling

Soil tests can be done to estimate the availability of plant nutrients and to adjust the amount of fertilizer for planting different crops using geotechnical, geochemical or ecological methods. Soil tests provide information on the soil's productivity potential, find the deficiency/sufficiency in nutrient levels, identify possible toxicities, and detect the presence of minerals (Agriculture-for-Impact, 2018). Certain elements may be absent for healthy plant production, or may be present at toxic levels. For example, acidic soils can be harmful to crop growth unless corrected (Noble-Research-Institute, 2018).

Soil tests combine a four-phase process, namely soil sampling, sample analysis, data interpretation and providing recommendations for managing soil properly (Agriculture-for-Impact, 2018). Through soil tests producers can manage soil types, topographic information, cropping history, manure application, fertilizer use, and irrigation systems. Zone and grid soil sampling are used most frequently in precision farming (Institute of Agriculture and Natural Resources-CropWatch, 2009). Soil sampling can optimize production, preserve the environment from pollution or contamination, identify plant culture problems, ameliorate the nutrient balance, reduce costs, and preserve energy by distributing fertilizer based on need. Producers can measure potential pH deficiencies, as well as salt and acid levels in the soil by analyzing soil testing results (USDA UMass Extension, 2018).

Soil test results interpret the suitability for growing different crops, and help understand the water-holding and drainage capacity of the soil (Sukendy, et al., 2016). Soil quality is vital for living ecosystems that support plants, animals, and humans (United States Department of Agriculture, 2018). Without doing a proper soil test, managing crop nutrients will be more difficult (Noble-Research-Institute, 2018). In a survey done by Mahler, et al. (2011), most responding producers noted that soil fertility counts for almost half of their crop production. Soil testing can play a vital role to monitor soil degradation and ground improvement (Adepetu, et al., 2000). Soil sampling in precision farming is an important precision tool available to ensure the effective use of nutrients in farming (Crozier and Heiniger, 2015).

3.2.3 Soil Mapping

A soil map is a small-scale map that contains survey reports and other information related to the soil (Hendricks, 2004). The global positioning system assists in record keeping of the soil variability with geospatial encoded data. Large databases created from GPS-based technology are available to producers (Neményi, et al., 2003). GPS plays a crucial role as it becomes an integral part of precision farming. To explain and analyze the sensor-based images, ground information is needed which can be collected from a variety of sites during grain production time.

In general, manually collected information is used to produce paper-based maps. Air maps can be collected from GPS or other sources in real time and converted to a digital format which is used in remote sensing. Soil data can be digitized using software and analyzed for different conditions for purposes of classification. Field data can be recorded directly into a digital database and combined with information on yield, soil, road, water, and related maps by analyzing sensor-based images. GPS connected hardware and software packages enable compilation of GPS signals and map-related information (Shanwad, et al., 2002). GPS-based soil maps help producers to better manage issues relating to soil fertility, allowing intensive and continuous production of different crops.

3.2.4 Variable Rate Technologies (VRTs)

Variable rate technologies are any type of technology allowing variable application of different elements. For example, VRTs can vary input application by area within a field. VRTs are used for many purposes such as varying the amount of fertilizer, seed planting density by different levels of soil moisture, using conservation tillage systems, using sensors to control weeds and pests, identifying different nutrient problems, and improving irrigation systems for water use optimization.

VRTs can reduce input usage and negative environmental effects, as well as improve production efficiency, and thereby may increase financial benefits for the producers. VRTs can be map-based, sensor-based or manual (Fulton, et al., 2009). VRTs minimize the use of pesticides, water, and other inputs, resulting in the environmental protection and ensuring good soil health (Fulton, et al., 2009).

VRTs reduce fertilizer usage by distributing different amounts of fertilizer across the field as needed by the soil. Soil zone application maps (with the help of software and GPS connection) are used to apply variable-rate technology to distribute fertilizer and other inputs (NDSU, 2013). A notable example from Glacier County, Montana is that without

VRTs, fertilizer cost was $36.85 per acre, reducing to $28.20 per acre after applying VRTs (Schaefer, 2007).

3.2.5 Auto Guidance Systems

Auto guidance systems are similar in concept to driverless vehicles. Auto guidance systems are used in precision agriculture to drive tractors and other equipment on defined tracks in real time, with the instructions given by producers and set up through GPS. Compared with manual steering systems, auto-steer is less labor-intensive. Auto-guidance systems can work in a straight line, bending position, complex situation and pivots, and it utilizes self-stabilization techniques for slopes (Hexagon-Agriculture, 2018).

Auto-steering systems are frequently used in planting, harvesting, cultivating and other types of field work. Auto-steering can help producers by decreasing manual labor, increasing efficiency, reducing fuel cost, saving time, and decreasing driver fatigue (Hexagon-Agriculture, 2018). Using auto-steer systems, crop producers may improve the available field resources and reduce soil compaction. However, compared to manual tractor systems, auto guidance systems are costly. Nevertheless, GPS-connected steering systems have been used extensively since economic benefits can be gained without integrating or adding different decision supports or systems component (McBratney, et al., 2005).

3.3 Agronomic Benefits of PATs

Agronomic benefits of precision agriculture include improved time management, enhanced input usage, advancements in crop health, and improved yields (Ling and Bextine, 2017). These claims are supported by Gralla (2018) and Meola (2016) who found that the Internet of Things (IoT) contributed to a yield increase of 1.75%, energy cost reductions of $7 to $13 per acre, and a decrease in irrigation water use of 8% for an average U.S. farm. Proper management of nitrogen under precision agriculture based on soil variability and productivity improve efficiency, yields, and agronomic efficiency (Khosla, et al., 2002).

In a study on two center-pivot irrigated cornfields in northeastern Colorado, Fleming, et al. (2001) assessed the economic feasibility and investigated the impact of VRT with grid soil sampling to gain an understanding of the productivity of land. They found that VRT application maps help increase productivity by identifying different management zones. In another study, Paz (2000) showed that water stress (drought or excess) explained approximately 69% of the variability in soybean yield over three years (1992, 1994 and 1996 in 207 grids within a 16 hectare field in Iowa. Irrigation management significantly increased these yields. Information management systems with the application of PATs customize crop variety and quality. At the same time, the information collected by using different precision tools (such as GIS, sensors, yield monitors) inform management decisions which help ensure agronomic benefits by employing improved soil management techniques and increased efficiency by minimizing cost (Harmon, et al., 2005).

3.4 Environmental Benefits

Most studies suggest that using fewer inputs under variable rate applications helps to maintain profits. Targeting fertilizer and pesticide usage benefits the environment by reducing losses due to nutrient imbalances, weed control, damage from insects, and excess use of inputs (Bongiovanni and Lowenberg-Deboer, 2004). In 2000, all crops (mainly cotton, tobacco, peanuts, corn, soybeans, wheat, and rice) planted in the southeastern United States using precision technology experienced a 6.7% increase in environmental quality, while other factors (profitability, total planting acres, computer use in farm, reducing input use, yield) remain constant at their mean level (Larkin, et al., 2015). Through fleet management and field robots, precision agriculture provides additional environmental benefits by preserving soil conditions and reducing energy costs (Auernhammer, 2001). The crop productivity and precise management of production factors (varieties of crop, harvest index, use of nitrogen, and investment in irrigation infrastructure), and environmental factors (soil conditions, plant ecology, and ecological intensification) determine the crop yield. The environmental benefits mainly come from site-specific management, plant density, nutrient pattern, pest control, irrigation management, spatial variability of soil properties, disease incidence, crop physiological status, remote sensing capabilities, etc. (Cassman, 1999). Practices of different PATs such as soil sampling, remote sensing, GIS, GPS, VRT, and measurement of soil electrical conductivity can improve yields and output quality, and reduce environmental effects by adjusting management practices and maintaining appropriate input levels of pesticides and fertilizers (Plant, et al., 2000). Remote sensing technology, optimal application of fertilizer, and use of soil-based moisture sensors to avoid the overuse of surface and ground water can help to ensure optimal soil moisture, soil fertility, weed control, pest control, and environmental impact (Harmon, et al., 2005).

3.5 Economics of Precision Agriculture

In their review of 11 studies on corn, soybeans, wheat, barley, and potatoes, Mulla and Khosla (2015) reported varying results. Four studies showed no improvements in profits, four produced mixed results, two reported improvements in profit and one was inconclusive due to the use of precision agriculture in various locations in the United States from 1991 to 1994. Among 108 papers on the profitability of precision agriculture done prior to 2000 listed by Lambert and Lowenberg-DeBoer (2000), 63% reported positive net returns, 11% of the studies reported negative net returns and 26% indicated mixed results.

Other studies reported after 2000 are discussed below. Larkin, et al. (2015) found that adopting PATs can improve profitability, and Castle, et al. (2017) also found a strong relationship between PATs adoption and profitability. However, this relationship could be spurious, as PATs adoption may drive profitability and vice versa.

In terms of specific types of PATs, Onofrio (2018) found that auto-swath technology can save an average of 4.3% on input costs and result in a payback of about two years. He also found that when producers include GPS guidance, their total cost savings were between 20% and 30%. According to Schimmelpfennig and Ebel (2016), relative to total per acre production costs, the estimated savings were 4.5% with yield mapping, 2.4% with GPS soil mapping, 2.7% with guidance systems, and 3.8% with VRT. Similar results were documented by Smith, et al. (2013), but in most cases the payback time was fewer than two years and the return on investment was greater than 50%. Similar results were reported by Johnson (2012) for swath control and seed command, which saved about 10% to 15% in seed costs, with a payback within the first year for larger farms and two to three years for small farms (Johnson, 2012). After subtracting the total cost of equipment, irrigation management under precision agriculture significantly increased net returns (Paz, 2000). Precision agriculture can increase the farms profits and increase the employment of skilled labor that positively influences the whole economy. Precision agriculture can reduce semiskilled and unskilled labor employment although it is likely to increase the net economic benefits (Plant, et al., 2000).

3.6 Factors Impacting the Precision Decision

Pierpaoli, et al. (2013) identified several factors that may influence farmers to adopt PATs, including ex-post and ex-ante assessment considerations, in addition to competitive and contingent factors (e.g. geography, size and soil quality), socio-demographic factors (such as age, education, computer confidence and information), and farmers' financial constraints (including income, whether he/she is a full-time farmer, ownership and tenure). In a review of ten selected studies, Tey and Brindal (2012) identified approximately 34 factors potentially influencing precision agriculture adoption. The authors grouped these factors into seven categories, namely socio-economic, agro-ecological, institutional, informational, farmers' perceptions, behavioral, and technological factors. In a separate report of 36 empirical studies, Antolini, et al. (2015) identified driving forces behind the adoption of precision technologies and reached similar conclusions with nearly identical factors. Further, Chen, et al. (2009) found that farmers are interested in adopting precision technology because they perceive that it can increase their operations' profitability and improve crop nutrient management. Thus, different characteristics of firms and farmers along with a variety of economic determinants influence farmers to adopt PATs.

3.7 Overall Trends

Using a spatial autoregressive model, Bongiovanni and Lowenberg-Deboer (2004) found that precision farming improves input usage and reduces the nutrient losses based on site-specific crop responses. However, not all PATs may be cost-effective or profitable at the same time. For example, a case study by Knight and Malcolm (2007) on 1,400 hectares of cropland in Australia showed that zone management technology under precision agriculture resulted in negative returns, while guidance technology produced positive returns. Experience from 299 Kansas farms under the Kansas Farm Management Association (Miller, et al., 2017) suggests that the profitability of adopting technologies depends on previously adopted other technologies. Among profit-earning farms, 87% to 98% adopted either precision soil sampling or variable rate fertility/seeding. PATs may help producers save money by increasing efficiency, reducing cost, and increasing adoption over time (Jochinke, et al., 2007). Variable-rate technologies can increase yields, save times, and save resources (Khosla, 2012). On-farm research in Colorado has shown that producers who use precision nitrogen management alone have reported increased net returns that vary from $17 per acre to $54 per acre. Effective input use by adopting technologies leads to increased crop yields in terms of both quantity and quality without disturbing the environment (Davis, et al., 1998).

Research based on a survey by Daberkow and McBride (2000) among over 8,400 farms concluded that only 4% of all farms adopted one or more PATs in their crop production in 2000. This study covered about 14% of planted acreage in the United States, or nearly 62 million acres. Though the amount of precision technology applied to crop production was relatively small, it has grown over time and may vary by crop, location or farm type. Grid sampling (2%) and variable rate technology in applying fertilizer (2%) were the most frequently adopted technologies for all farms, while yield monitoring (1%) and yield mapping (1%) were the least-frequently adopted precision technology in 1998. Remote sensing technology and variable rate technology usage in seed and pesticide applications were less than 1% reported. Corn and soybeans were the two crops with the most frequently adopted PATs. Farm size (in terms of total crop sales of produced crop) directly related to adopting precision farming technology. Among farms that adopted PATs, 18% sold more than $500K while only 2% of farms sold less than $100K.

Antolini, et al. (2015) found that large farms are more likely to adopt technology than small ones due to economies of scale. Producers with relatively high levels of education had relatively high rates in adoption of technologies and older producers were comparatively unlikely to adopt. Adopters were also likely to have additional non-farm income. The availability of financial sources for technology purchase can lead to the adoption of additional precision farming technology. Joining a producers' association helped in the adoption of additional technology as they gained experience from others and were influenced by adopters. Awareness and easy access to information helped in the adoption of more technologies, while negative perceptions about technologies lead to reduced adoption rates.

In 2013, a mail survey was performed by the National Cotton Council of America (Zhou, et al., 2017) to assess precision technology adoption trends in the main cotton-producing areas of the 14 southern states in the US. The report suggested that 40.9% of the surveyed producers used spatial information gathering, 67% used guidance technology with global positioning systems, 25.3% used variable rate application technology and

29.3% had adopted automatic section control systems. About 42.5% of the producers used yield monitoring bundled with GPS and grid soil sampling. It is noteworthy that precision technology adoption rates among cotton producers in the Corn Belt were higher than those in the Mississippi Delta, Northern Plains and Southern Plains areas. Among all precision technologies, the GPS with guidance and variable rate technology were adopted the most in the Corn Belt area. Information gathering systems were used widely in the Mississippi Delta region, while automatic section controls were heavily used in the Appalachian region.

In their review of 108 studies, Lambert and Lowenberg-DeBoer (2000) report that for a given technology used in precision agriculture, 63% had net positive returns, 11% had negative returns and 26% had mixed results. Precision agriculture adoption trends suggest that these practices have gradually increased over time in all parts of the United States. The report prepared by Schimmelpfennig and Ebel (2011) based on the Agricultural Resources Management Survey (ARMS) spanning over 10 years across the United States concluded that yield monitoring systems were used in over 40% of the crop area and between 40% and 45% for the corn and soybean planted acres in 2005 to 2006. The adoption rate of variable rate application for mixed purposes, namely for seeders, sprayers, fertilizers, and pesticides, was comparatively low and almost flat for corn and soybeans but increased over time. At the national level, adoption rates of guidance systems using GPS varied between 15% and 35% for corn, soybeans and winter wheat from 1996 to 2009. Adoption rates also varied across geographical locations. Between 1998 and 2006, adoption rates of variable rate technology and guidance systems in corn acreage were higher than in soybeans acreage across the United States. Surprisingly, the use of GPS has declined over time in all major crops due to GPS mapping errors, after showing relatively high adoption rates during the period between the late 1990s and 2001 (Schimmelpfennig and Ebel, 2011).

CHAPTER 4

DATA AND METHODS

4.0 Conceptual Framework

Producers maximize their utility from crop production when they reduce costs by choosing a different combination of inputs. To operate a farm, producers need to consider fixed or variable costs or both. Both costs depend on input usage. PATs can reduce input costs by ensuring the efficient use of inputs such as seed, fertilizer, and other chemicals. Precision technologies are costly and increase the fixed costs, including those associated with human capital development. Also, they incur variable costs as they need to update and repair the technologies over time (Tamás, 2011). Proper use of precision technologies can reduce production uncertainty, increase yields, and improve soil health, water, and air quality (Cassman, 1999). Although short-term costs will increase, the adoption decision may provide long-term benefits (Brennan, et al., 2007).

A producer adopts one or more PATs when his or her utility increases by using the technologies. A producer's PAT adoption decision depends not only on net returns, but also on his or her socio-economic characteristics and other factors (Daberkow and McBride, 2003).

The random utility model is an alternative interpretation of data on individual choices (Greene, 2003). The random utility framework was introduced to determine the probability that a producer would choose to adopt a precision technology. Ben-Akiva (2008) defines the random utility model as follows:

$$U_{in} = V_{in} + \mathcal{E}_{in}, \ \ i = 1, \dots \dots .. I \text{ and } n = I, \dots, N, \qquad (1)$$

where U_{in} is the n^{th} producer's highest expected utility accruing from choosing alternative i, V_{in} is the systematic utility that would be maximized (the deterministic part), and $\mathcal{E}_{in}$ is the random utility (the stochastic part). The probability that a producer n chooses alternative i is given by

$$\begin{aligned} P_n(i) &= \Pr\left(U_{in} \geq U_{jn}\right) \\ &= \Pr\left(V_{in} + \mathcal{E}_{in} \geq V_{jn} + \mathcal{E}_{jn}\right) \\ &= \Pr\left(\mathcal{E}_{jn} - \mathcal{E}_{in} \leq V_{in} - V_{jn}\right) \text{ for all i, } i \epsilon C_n, \end{aligned} \tag{2}$$

where C_n is the choice set for participants $n[C_n = \{i, j\} = \{\text{Adopt, Don't Adopt}\}]$. Ben-Akiva (2008) showed that the probability of producer n choosing alternative i reduces to

$$P_n(i) = \frac{e^{\mu V_{in}}}{\sum_{j \epsilon C_n} e^{\mu V_{jn}}}, \text{ where } \mu > 0. \tag{3}$$

The utility function of producers can be written as follows. Let $Y_i = 1$ denote the decision of producer i to adopt a precision technology or a bundle of precision technologies and let $Y_i = 0$ denote the decision to not adopt the technology. Let the perceived profit associated with adoption decisions be denoted by $\pi_i^{Y_i}$. The relative net profit from adopting the technology is defined as

$$\Delta\pi_i = \pi_i^1 - \pi_i^0. \tag{4}$$

Let U_i^{yi} denote the utility for producer i from decision Y_i. Adoption occurs when

$$E(U(1, \pi_i^1, X)) > E(U(0, \pi_i^0, X)), \tag{5}$$

where X is a vector of observable covariates.

The producer's utility function $U(Y_i, \pi_i^{Y_i}; X)$ is unknown, and the deterministic part of the utility function is $V(Y_i, \pi_i^{Y_i}; X)$. Thus, the inequality in (5) can be written as

$$V(1, \pi_i^1, X) + U_1 > V(0, \pi_i^0, X) + U_0, \tag{6}$$

where U_1 and U_0 are independently and identically distributed random disturbances with zero means and unit variances. Here, characteristics can be socio-demographic characteristics such as age, spouse non-farm income, educational status, participation in government programs, and other factors.

For this study, vector X consist of characteristics including age, participation in the Conservation Stewardship Program, ownership of a cattle operation, education, size of cropland acres, spouse non-farm income, service issues due to distance problem, reliance on information from a farm dealer, and and computer usage for accounting purposes.

4.1 Survey Description

The data for this study were collected from a farm-level survey conducted in eastern South Dakota during the spring of 2017. The survey contained four types of information related to the farm operations, their conservation agriculture practices, PAT usage, and operator characteristics. This study mainly focuses on the determinants of precision technologies including auto-steer, variable rate technology, automatic section control, grid soil sampling, prescription field maps, yield maps, yield monitor, crop tissue sampling, GPS guidance system, and satellite/aerial imagery. The information on precision technologies includes the year of first use, used by whom (user, consultant or custom applicator), and which crops were produced (corn, soybeans, and wheat). The questionnaire included questions related to reasons for adopting decision of precision technologies and other relevant issues about servicing the technologies. Future adoption of precision technologies, different types of risk sources, and uses of different risk management tools were also included within the survey.

The remainder of the survey included farm location, distance of the farm to service locations, ownership and amount of land, amount of cropland enrolled in different programs, number of harvested acres for different types of crops, and cattle-related information. Also included was information on conservation practices such as crop rotation practices, grazing cover crops and/or crop residue, reasons for using conservation practices, various tillage systems and the importance of using or not using different conservation practices, age, income and education of the operator, the nature of non-farm employment, as well as computer, iPad, and smartphone usage.

Sample respondents were selected based on the ten highest corn, soybean, and wheat-producing counties in South Dakota in 2015. 1,200 questionnaires were sent to agricultural producers in 14 primary counties, dated January 27, 2017. After receiving the questionnaires, 199 surveys contained usable data, 37 were not delivered, and 59 were returned with no or insufficient data.

Table 6. List of the variables

Variable Name	Definition
APAT	Adoption of precision agriculture technologies. Use of at least one of the top six popular technologies (Yes = 1, No = 0).
NUMTECH	Precision Technology Bundle. Use of a total number of technologies (None = 0, All technologies = 6).
AGE	Age of the respondents (in years).
CSP	Participation in the Conservation Stewardship Program in South Dakota. Cost share or incentive payments received in 2016 for participating Conservation Stewardship Program (Yes = 1, No = 0).
CATTLE	Having ownership in beef cow-calf or beef feeder (dairy or beef) or dairy-cow or replacements operations (Yes = 1, No = 0).
EDUCATION	Level of education (Less than high school/GED or High school/GED or Some college = 0, Occupational/Associates Degree or Bachelor's Degree or Graduate/Professional Degree = 1).
CROPLANDACRES	Area of cropland in acres.
SPOUSEOFFFARM	Off-farm income of the spouse (Yes = 1, No = 0).
SERVICEISSUE	Distance issue due to service/repair PATs (Yes = 1, No = 0).
INFOFD	Using a farm dealer as information source for PATs (Yes = 1, No = 0).
TECHACCT	Use of computer in accounting purpose. If used a computer in accounting activities (Yes = 1, No = 0).

Source: Deutz (2018).

4.2 Variable Selection

A list of variables included in the analysis are explained in greater detail in the following sections.

4.2.1 Adoption of Precision Agriculture Technologies (APAT)

In the survey, use of auto-steer, variable rate systems, automatic section control/shut-offs, grid soil sampling, prescription field maps, crop tissue sampling, yield monitor, aerial/satellite imagery, and GPS guidance system-related information was gathered. This study focuses on the top six technologies (variable-rate system, yield monitor, GPS guidance system, automatic section control/shut-offs, prescription field maps and auto-steer) according to their popularity among the sample producers. Variable PAT takes the value of 1 if any one of the top six technologies is adopted by the producers and 0 otherwise. That is, 0 means producers are not adopting none of the top six technologies. This variable is a response variable in the Probit model.

4.2.2 Precision Technology Bundle (NUMTECH)

In order to identify the factors influencing the intensity of the adoption of precision technologies, a count variable (NUMTECH) was created by adding the top six precision technologies for each observation. The range of the precision technology bundle count is from 0 to 6, so if a producer did not adopt any of the precision technologies, then the precision technology bundle for that producer will be 0. For a producer adopting all of the top six technologies, the precision technology bundle will be 6. This count variable will be used in the Poisson regression as a response variable.

4.2.3 Age (AGE)

Age is an important producer characteristic. In the survey, the average age of the producers was 58 years old with a standard deviation of 12 years. The youngest producer age was 28 years, while the highest producer age was 92 years. It was assumed that older producers are less likely to adopt precision technologies, in accordance with Daberkow and McBride (2003).

4.2.4 Conservation Stewardship Program in South Dakota (CSP)

The survey also collected information on cost-share or incentive payments in 2016 for conservation practices implemented. Several program practices were utilized among the producers, such as the Conservation Stewardship Program (CSP), the Environmental Quality Incentive Program (EQIP), comprehensive nutrient management, state programs, and others. Among the programs, the CSP is the largest working-lands conservation program in the United States. The CSP started as the Conversion Security Program in 2002, a complex watershed-based pilot project with just 2 million acres in its first year. This evolved into a nationwide program, enrolling over 70 million acres since 2010 (Natural Resources Conservation Service, 2016). The CSP is available in tribal areas, private agricultural lands, and nonindustrial private forest lands. It influences land stewardship and seeks to improve conservation performance. In South Dakota, the priority concerns are related to soil erosion, soil and water quality degradation, plant condition degradation, and fish and wildlife habitat (Fox and Johnson, 2018). CSP participation is expected to positively influence the adoption decision of precision technology, based on the earlier findings by Deutz (2018).

4.2.5 Cattle Operation (CATTLE)

The questionnaire included several cattle-related questions. Three types of cattle ownership were considered, including beef cow-calf, beef-feeders (dairy or beef), and dairy cows or replacement operations. A binary variable was introduced by using these three types of cattle. If a producer owned any one type of these cattle categories, then the cattle variable has a value of 1, and otherwise 0. Based on the findings of Deutz (2018), it is expected that cattle producers are relatively less likely to adopt precision technology.

4.2.6 Education (EDUCATION)

Education is an important factor influencing precision technology adoption decisions. Education levels can impact the adoption decision both negatively and positively (Banerjee, et al., 2008, Deutz, 2018, Paxton, et al., 2010, Sevier and Lee, 2004 b). Relatively highly educated individuals may be comparatively more efficient and may have the needed skills to employ precision technology. However, relatively highly educated individuals may have income sources or professions in addition to farming and may therefore be less likely to adopt precision technologies.

4.2.7 Cropland Acres (CROPLANDACRES)

Each producer, on average, was found to hold approximately 1913.49 acres in non-hay cropland, cropland pasture, and land in government programs. In general, the use of precision technology is more convenient and cost-effective for larger farms than for smaller ones, because applying precision technology on a large operation can take advantage of economies of scale. Therefore, it is expected that PAT adoption rates are higher for larger than for smaller farms, in accordance with earlier findings by Banerjee, et al. (2008), Castle, et al. (2016).

4.2.8 Spouse Non-Farm Income (SPOUSEOFFFARM)

Fernandez-Cornejo, et al. (2007) found that the relationship between the adoption of yield monitors and non-farm household income was negative and statistically significant. That is, decreasing non-farm income was associated with an increased probability of adopting yield monitors. These findings are consistent with anecdotal evidence suggesting that precision farming techniques in general are managerially complex. Additional income from a spouse may make operators more reluctant to adopt new precision technology. As a result, spousal non-farm income is expected to negatively influence the precision technology adopting decision.

4.2.9 Service Issue Related to Precision Technology (SERVICEISSUE)

The survey also collected information on access to PAT service and maintenance, measured in distance from a service center. The average distance to the nearest place to service technology tools was approximately 26 miles, with a standard deviation of approximately 23 miles. Overall, distances to a service facility ranged from less than 1 mile to 175 miles. . It is expected that the producers will be more reluctant to adopt precision technology and get their equipment serviced when they are far removed from a service location, while producers' adoption will be relatively high for those with nearby access to service.

4.2.10 Information from Farm Dealer (INFOFD)

Information is a powerful tool in the modern economy, and it plays a vital role in the PAT adoption process. Because farm dealers specialize in services that complement PATs, they not only serve as information sources, they influence producers to adopt PATs. Producers were asked which information sources they rely on in the PAT adoption decisions. Farm dealers, crop consultants, agricultural extension agencies, other farmers, other families, trade shows, news media, and government agencies such as the NRCS were listed as possible options. Farm dealers were the most popular information source among the respondents, consistent with findings by Fountas, et al. (2005). Farm dealers tend to reach many producers because of their business interests, so they have a significant influence on producers when considering PAT adoption decisions.

4.2.11 Use of Computers for Accounting Purposes (TECHACCT)

Like other businesses, agricultural producers use accounting methods to produce financial statements, file accurate tax returns, and apply for financial support from the government. Producers frequently use computer software such as Microsoft Excel for their accounting and other transactions needs. The use of computers for accounting purposes was chosen as a determinant of PAT adoption decisions, and would be expected to positively influence the adoption possibility (Banerjee, et al., 2008). Table 7 summarizes the initial statistical results for each variable.

Table 7. Summary Information of Variables

Variable	Mean	Std. Dev.	Min	Max
APAT	0.86	0.34	0	1
NUMTECH	3.06	2.63	0	6
AGE	58.54	12.19	28	92

CSP	0.22	0.41	0	1
COLLEGEEDUCATION	0.45	0.49	0	1
CATTLE	0.52	0.50	0	1
CROPLANDACRES	1,913.49	2,369.08	0	13,850
SPOUSEOFFFARM	0.51	0.50	0	1
SERVICEISSUE	0.29	0.46	0	1
INFOFD	0.64	0.48	0	1
TECHACCT	0.64	0.48	0	1

Source: Deutz (2018)

4.3 Selected Survey Summary

In the survey, a total of nine technologies were listed. Among the 199 responses, the GPS guidance system was the most popular technology, followed by auto-steer and yield monitors. The popularity of automatic section control/shut-offs is higher than those of variable rate systems and prescription field maps. Table 8 lists the PATs with the average year of first use and mean of adopted technologies. Grid soil sampling and crop tissue sampling were used by only 89 and 75 producers, respectively, out of a total 199 producers. The least popular technology was aerial/satellite imagery.

Table 8. PATs with Average Year of First Use among 199 Producers

Precision Technology	Total Users	Mean Use	First Usages Year on Average	Percentage of Users
GPS Guidance System	151	0.89	2008	75.88
Auto-steer	147	0.79	2008	73.87
Yield Monitor	136	0.84	2006	68.34
Automatic Section Control/Shut-offs	110	0.62	2011	55.28
Variable Rate System	100	0.58	2010	50.25
Prescription Field Maps	100	0.66	2011	50.25
Grid Soil Sampling	89	0.59	2009	44.72
Crop Tissue Sampling	75	0.50	2012	37.69
Aerial/Satellite Imagery	61	0.43	2009	30.65

Source: Deutz (2018)

Among all adopters, the mean of GPS guidance systems use was about 0.89 where 1 indicates the use of GPS guidance systems and 0 indicates the lack thereof. The means of the uses of yield monitor, auto-steer, prescription field maps, automatic section control/shut-offs, and grid soil sampling were 0.84, 0.79, 0.66, 0.62 and 0.59, respectively. The means of the variable rate systems, crop tissue sampling and aerial/satellite imagery were 0.58, 0.5 and 0.43, respectively. These are the lowest among all precision technologies listed in Table 8.

The average year of the first use for yield monitors – which was the earliest adopted precision technology – was 2006. The latest adopted technology was crop tissue sampling, in 2012. The second latest adopted technologies were automatic section control/shut-offs and prescription field maps and their average year of first use was 2011. On average, grid soil sampling and aerial/satellite imagery were first used in 2009. Auto-steer, variable rate technology, and GPS guidance systems were on average first used in 2008, 2010 and 2008, respectively.

Among all respondents, 73.9% used auto-steer, 50.3% used variable rate systems, 55.3% used automatic section control/shut-offs, 44.7% used grid soil sampling, 50.3% used prescription field maps, 37.7% used crop tissue sampling, 68.3% used yield monitor, 30.7% used aerial/satellite imagery, and 75.9% used GPS guidance systems.

4.3.0 Age

Age-related information is shown in Table 9 with a summary of adopters and non-adopter according to their age. Information about year of birth was collected in the survey. The data was converted to age and divided into six age groups. Most survey participants were between age 51 to 60 years of age; the smallest group of participants were 30 years old or less.

Table 9. Precision Technology Adopters vs Non-Adopters, By Age

Age Group	Total Participants	Non Adopters	Adopters	Total Participants (%)	Total Non-Adopters (%)	Total Adopters (%)
< 30	4	0	4	2.01	0.00	100.00
31 to 40	14	0	14	7.04	0.00	100.00
41 to 50	24	5	19	12.06	20.83	79.17
51 to 60	64	7	57	32.16	10.94	89.06
61 to 70	57	6	51	28.64	10.53	89.47
> 70	31	9	22	15.58	29.03	70.97
Age N/A	5	0	5	2.51	0.00	100.00

Source: Deutz (2018)

It is interesting that all younger producers are precision technology adopters, while most of the non-adopters are older producers. There were about 64 (32.16%) participants from the 51 to 61 age group, 57 (28.64%) participants from the 61 to 70 age group, 31 (15.58%) participants from the 70+ age group, 24 (12.06%) participants from the 41 to 50 age group, 14 (7.04%) participants from the 31 to 40 age group, 4 (2.01%) participants from the 30 and below age group, and 5 (2.51%) participants did not report their age. The highest number of adopters was 57, which falls into the 51 to 60 age group, while the lowest number of adopters, 4 falls into the 30 and below age group. According to data on non-adopters, it can be said that the highest portion of non-adopters, 9, falls into the 70+ age group which is the highest age group among all six age groups. All producers younger than 40 years old adopted precision technology, as did the producers who did not provide age information.

4.3.1 Education

Table 10 represents the participants' information on their level of education. Education-related data was collected with six categories ranging from less than high school to a professional degree. Most of the participants, 57 (28.64%), claimed to have at least a high school or GED degree while 6 (3.02%) participants did not. Only one participant in the survey, a PAT adopter, did not report an education level.

Table 10. Comparison of PAT Adopters vs Non-Adopters, by Education Level

Education Level	Total Participants	Non Adopters	Adopters	Total Participants (%)	Total Non-Adopters (%)	Total Adopters (%)
Less than High School/GED	6	1	5	3.02	16.67	83.33
High School/GED	57	6	51	28.64	10.53	89.47
Some College Degree	45	4	41	22.61	8.89	91.11
Occupational/Associate Degree	27	5	22	13.57	18.52	81.48
Bachelor's Degree	53	8	45	26.63	15.09	84.91
Graduate/Professional Degree	10	3	7	5.03	30.00	70.00
Missing Education	1	0	1	0.50	0.00	100.00

Source: Deutz (2018)

There were 45 (22.61%) participants who had some college degree, 27 (13.57%) participants who had an occupational or associate degree, and 10 (5.03%) who had a graduate or professional degree. The highest number of non-adopters (8) held bachelor's degrees while the highest number (51) held high school or GED degrees. At each education level, most participants adopted precision technologies. The lowest number of adopters (5) and non-adopters (1) held the lowest level of education which was less than a high school degree or GED. At the lowest education level, , 83% of the producers adopt precision technologies while at the highest levels, 70% are PAT adopters.

4.3.2 Income

Table 11 compares producer income levels between PAT adopters and non-adopters. To account for producer reluctance to provide sensitive income-level information, the survey estimates producer income across a range of 6 levels.

Table 11: Comparison of PAT Adopters vs Non-Adopters by Total Yearly Income Level

Income Level	Total Participants	Non Adopters	Adopters	Total Participants (%)	Total Non-Adopters (%)	Total Adopters (%)
Less than $149,999	28	13	15	14.07	46.43	53.57
$150,000 - $399,999	35	8	27	17.59	22.86	77.14
$400,000 -$749,999	33	4	29	16.58	12.12	87.88
$750,000 -$1,499,999	48	0	48	24.12	0.00	100.00
$1,500,000 - $2,499,999	20	1	19	10.05	5.00	95.00
$2.5 million or more	16	1	15	8.04	6.25	93.75
Income N/A	19	0	19	9.55	0.00	100.00

Source: Deutz (2018)

Most of the participants, 48 (24.12%), come from the $750,000 to $1,499,999 income group and all of them adopted precision agriculture technology while the lowest number of participants, 16 (8.04%), comes from $2.5 million or more, the highest level among all of the income groups and 94% adopt precision technologies. There are 28 (14.07%) participants in the lowest income range of less than $149,999. Of those participants, 46% participants were not adopting any precision technology and 54% participants adopted precision technologies which is the lowest percentage among all adopters from other income levels. From the highest income level, only 6% participants were not adopting any precision technology while 94% were adopt precision technologies. There are 19 (9.55%) participants in the survey who did not disclose their income level and all of them adopted precision technologies.

4.3.3 Daily Activities

Table 12 represents different farm-related daily activities. Participants were asked about their use of computers, iPads, and smartphones.

Table 12: Activity List

Name of Activity	Total Activity User	Total Activity User (%)
User of computer in accounting purpose	127	63.82
User of computer in record keeping purpose	135	67.84
User of computer in farm supplies and purchases purpose	100	50.25
User of computer in obtain marketing information purpose	142	71.36
User of I-pad/smart phone in soil testing purpose	36	18.09
User of I-pad/smart phone in field scouting purpose	46	23.12
User of I-pad/smart phone in soil rain monitoring purpose	84	42.21
User of I-pad/smart phone in market information purpose	142	71.36

Source: Deutz (2018)'s survey

Among all participants (199) in the survey, 142 (71.36%) used computers to obtain marketing information, with similar numbers using iPads or smartphones. The smallest number of participants, 36 (18.09%), used iPads/smartphones for soil testing purposes. Computers were used by 127 (63.82%) participants for accounting purposes. The number of participants using computers for record-keeping and managing/purchasing farm supplies was 135 (67.84%), and 100 (50.25%), respectively. For in-field scouting purposes, iPads or smartphones were used by 46 (23.12%) participants, while 84 (42.21%) participants used these devices for precipitation monitoring. Overall, Table 12 shows that computers were used more often among producers than iPads or smartphones for overall listed activities.

4.4 Comparison of Means between Adopters and Non-adopters

In inferential statistics, t-tests are used to identify statistically significant differences in the means of two groups. The sample mean differences between producers who adopt or do not adopt any PAT were evaluated by way of two-tailed t-tests. The null hypothesis of no significant difference between adopters and non-adopters was set for sample means as follows:

$$H_0: \tilde{x}_A = \tilde{x}_{NA} \tag{7}$$

The alternative hypothesis of the existence of a significant difference between adopters and non-adopters is:

$$H_0: \tilde{x}_A \neq \tilde{x}_{NA} \tag{8}$$

In both hypotheses, subscripts A and NA represent producers who adopt and do not adopt any one of the precision technologies, respectively.

To perform the hypothesis test, the following test statistic was calculated:

$$t^* = \frac{\tilde{x}_A - \tilde{x}_{NA}}{s_p^2 \sqrt{{}^1/_{N_A} + {}^1/_{N_{NA}}}}, \tag{9}$$

where $\tilde{x}_A$ and $\tilde{x}_{NA}$ are the sample means of producer characteristics for users and non-users of PATs, respectively, N_A and N_{NA} are the sample sizes of adopters and non-adopters of PATs, respectively, and s_p^2 is the sample variance. The sample variance is found by using the following formula:

$$s_p^2 = \frac{(N_A - 1)s_A^2 + (N_{NA} - 1)s_{NA}^2}{N_A + N_{NA} - 2} \tag{10}$$

4.5 Correlation Matrix

Pairwise correlations were examined to identify potential multicollinearity effects. If present, multicollinearity can reduce the precision of the estimated coefficient and p-values.

Table 13. Pairwise Correlation Among Independent Variables

VARIABLES	AGE	CSP	CATTLE	EDUCATION	CROPLANDACRES	SPOUSEOFFFARM	SERVICEISSUE	INFOFD	TECHACCT
AGE	1								
CSP	-0.14	1							
CATTLE	-0.05	-0.03	1						
EDUCATION	-0.18	0.09	-0.05	1					
CROPLANDACRES	0.13	0.14	0.07	-0.07	1				
SPOUSEOFFFARM	-0.51	0.13	0.05	0.12	-0.08	1			
SERVICEISSUE	0.12	-0.10	-0.12	0.10	-0.05	-0.02	1		
INFOFD	-0.13	0.12	0.07	-0.02	0.06	-0.01	-0.27	1	
TECHACCT	-0.34	0.14	-0.04	0.19	-0.09	0.19	-0.04	0.17	1

Source: Deutz (2018)’s survey.

The pairwise correlations establish the relationships between independent variables. Table 13 shows that the highest absolute correlation is -0.50 between age and spousal non-farm income. Most correlation coefficients are are less than 0.20. Because there are no highly correlated predictor variables, the estimations are expected to be efficient.

4.6 Probit Model

The conceptual model described above can be represented as the following latent equation:

$$Y_i^* = \beta' X_i + \epsilon_i \quad (11)$$

Assuming the random errors in (11) are independent and identically distributed across the I alternatives and N individuals as a Type I extreme value distribution, then $\mathcal{E}_n = \mathcal{E}_{jn} - \mathcal{E}_{in}$ in (2) is logistically distributed. However, we observe only the binary outcome Y_i (whether farmer i has adopted the technology or not), and (11) can be empirically estimated using a univariate probit model that uses maximum likelihood estimation:

$$Y_i = \beta' X_i + \epsilon_i \tag{12}$$

In the probit model, there is a latent and unobserved continuous variable y*, eventhough discrete values of 0 and 1 are observed.

$$y^* = \sum_{K=1}^{K} \beta_K X_K + \mathcal{E} \left(\text{where } \mathcal{E} \text{ is } \mathrm{IN}(0, \sigma^2)\right) \tag{13}$$

The dependent variable, y, is observed and determined by y* as follows:

$$y = \begin{Bmatrix} 1 \text{ if } y^* > 0, \\ 0 \text{ otherwise} \end{Bmatrix} \tag{14}$$

The point of interest relates to the probability that y equals one. From the previous equations, it follows that

$$\begin{aligned} \mathrm{Prob}(y = 1) &= \mathrm{Prob}(\sum_{K=1}^{K} \beta_K X_K + \mathcal{E} > 0) \\ &= \mathrm{Prob}(\mathcal{E} > -\textstyle\sum_{K=1}^{K} \beta_K X_K) \\ &= 1 - \phi(-\textstyle\sum_{K=1}^{K} \beta_K X_K)\ , \end{aligned} \tag{15}$$

where ϕ is the cumulative distribution function of $\mathcal{E}$ (Liao, 1994).

In the probit model, it is assumed that the data are generated from a random sample of size N with sample observations denoted by i, where i = 1, 2….., N. As a result, the y_i must be statistically independent. The Probit model also assumes that the independent variables are randomly distributed, and that there is no linear dependence among the X_{ik}'s. This indicates that N > K, meaning each X_k has some variation across observations and that they are not perfectly correlated. To estimate the Probit parameters, the Maximum

Likelihood Estimation (MLE) method is used. MLE focuses on choosing parameter estimates that give the highest probability or likelihood of observing data. The main principle of MLE is to choose as an estimate β the set of K numbers that would maximize the likelihood of having observed this particular y. The main advantage of ML estimators is that among all Consistent Asymptotically Normal Estimators, MLEs have optimal asymptotic properties (Aldrich and Nelson, 1984, Briggs, 2003, Greene, 2003).

The following probit model was specified to identify the relationship between the response variable and explanatory variables. The dependent variable is a binary variable with values of 0 or 1, depending on whether the producers adopted at least one technology or not. Assuming that V_i and V_j are the linear in their parameter, the indirect utility function of alternative i (i=1) for the respondent to be estimated is given by

$$\begin{aligned} \mathrm{APAT_i} = {} & \beta_0 + \beta_1\mathrm{AGE_i} + \beta_2\mathrm{CSP_i} + \beta_3\mathrm{CATTLE_i} + \beta_4\mathrm{EDUCATION_i} + \beta_5\mathrm{CROPLANDACRES_i} \\ & + \beta_6\mathrm{SPOUSEOFFFARM_i} + \beta_7\mathrm{SERVICEISSUE_i} + \beta_8\mathrm{INFOFD_i} + \beta_9\mathrm{TECHACCT_i} + \mathcal{E}_i \end{aligned} \tag{16}$$

4.7 Count Model

It is hypothesized that factors determining the adoption decision could be different from those determining the intensity of adoption, measured here as the number of technologies adopted. Understanding the factors determining the intensity of adoption is helpful for devising programs and policies to scale up the adoption of precision technology bundles.

To measure the intensity of adoption by observing the number of technologies adopted, this study uses the Count Model. To determine the number of total adopted PATs by each respondent in the survey, the variable NUMTECH was developed. This is the dependent variable in a Poisson regression model that adds the number of different precision technologies adopted by producers. This variable takes values ranging from 0 to 6, with 0 indicating the producer does not use any PATs and 6 indicating the producer uses all technologies.

NUMTECH is a non-negative integer with a small mean value. In such cases, the response variable Y has a Poisson distribution. In Poisson regression, based on the input variables, the aim is to predict the count variable (the dependent variable). As counts follow the Poisson distribution, the mean and variance are assumed to be the same. It is also assumed that all observations are independent of each other. The probability distribution function of the Poisson is given by:

$$f(Y_i) = \frac{\mu^Y e^{-\mu}}{Y!} (\text{where } Y = 0, 1, 2, \dots \dots \dots) \tag{17}$$

Here, f(Y) is the probability that the variable Y takes a non-negative integer value, and μ is the average count of events. The Poisson regression model may be written as follows:

$$Y_i = E(Y_i) + u_i = \mu_i + u_i \tag{18}$$

The Y_i are independently distributed random variables with mean μ_i expressed as

$$\mu_i = E(Y_i) = \beta_1 + \beta_2 X_{2i} + \beta_3 X_{3i} + \cdots + \beta_k X_{ki} \tag{19}$$

The X_i are some of the variables that might affect the mean value. For estimation purposes, the model can be written as

$$Y_i = \frac{\mu^Y e^{-\mu}}{Y!} + u_i \tag{20}$$

Replacing μ with (18), the resulting regression model is non-linear in the parameters, necessitating non-linear regression estimation (Gujarati, 2004). The equation the index uses for applying the Poisson regression, is as follows:

$$\mathrm{NUMTECH_i} = \beta_0 + \beta_1\mathrm{AGE_i} + \beta_2\mathrm{CSP_i} + \beta_3\mathrm{CATTLE_i} + \beta_4\mathrm{EDUCATION_i} + \beta_5\mathrm{CROPLANDACRES_i} + \beta_6\mathrm{SPOUSEOFFFARM_i} + \beta_7\mathrm{SERVICEISSUE_i} + \beta_8\mathrm{INFOFD_i} + \beta_9\mathrm{TECHACCT_i} + \mathcal{E}_i \quad (21)$$

4.8 Negative Binomial Regression

The major shortcoming of Poisson regression is that the mean and variance are assumed to be equal, but in practice may not be (Greene, 2003). Especially for count data, this equality assumption is not reasonable. In some cases, the conditional variance is larger than the conditional mean which is known as over-dispersion. The negative binomial regression is suitable in this situation and it combines the Poisson regression and the gamma distribution. This type of regression allows the mean to differ from variance. To address over-dispersion, the Poisson regression must be modified by adding an error term in the model such that:

$$\mu = e^{\sum_{j=1}^{K} \beta_j X_{ji} + \varepsilon_i} \quad (22)$$

A full negative binomial model can be written as follows:

$$P(y|X) = \frac{\Gamma(y + \alpha^{-1})}{y!\,\Gamma(\alpha^{-1})} \left(\frac{\alpha^{-1}}{\alpha^{-1} + \mu}\right)^{\alpha^{-1}} \left(\frac{\mu}{\alpha^{-1} + \mu}\right)^{y}, \quad (23)$$

where α represents the extent of dispersion. If α is zero, then the model will act as a Poisson regression. Equation 1 is a fundamental form of the binomial distribution. The dependent variable in a negative binomial regression model is an integer variable that takes values ranging from 0 to 6 and the index is as follows:

$$\mathrm{NUMTECH_i} = \beta_0 + \beta_1\mathrm{AGE_i} + \beta_2\mathrm{CSP_i} + \beta_3\mathrm{CATTLE_i} + \beta_4\mathrm{EDUCATION_i} + \beta_5\mathrm{CROPLANDACRES_i} + \beta_6\mathrm{SPOUSEOFFFARM_i} + \beta_7\mathrm{SERVICEISSUE_i} + \beta_8\mathrm{INFOFD_i} + \beta_9\mathrm{TECHACCT_i} + \mathcal{E}_i \quad (24)$$

4.9 Estimating Marginal Effects

It is common to generate the marginal effects after reporting the coefficient from the estimation results of probit, Poisson, and negative binomial models. The marginal effects reflect the change in the probability of y=1 given a unit change in an independent variable x. An increase in x increases (decreases) the probability that y=1 by the marginal effect, expressed as a percentage. For dummy independent variables, the marginal effect is expressed in comparison to the base category (x=0). For continuous independent variables, the marginal effect is expressed for a one-unit change in x.

It is important to report the marginal effect of the probit, Poisson, and negative binomial models: while the magnitude of the estimated parameters is not directly explainable, the sign is. Usually, there are two types of marginal effects: the marginal effects at the mean and average marginal effects. The marginal effects at the mean are estimated for the average person in the sample.

$$\frac{dp}{dx_j} = F'(x'\beta)\beta_j \tag{25}$$

On the other hand, the average marginal effects are estimated as the average of the individual marginal effects.

$$\frac{dp}{dx_j} = \frac{\sum F'(x'\beta)}{n}\beta_j \tag{26}$$

Although the marginal effects at the mean are used in most studies, this study includes the average marginal effects because of their explanatory capability. In marginal effects, the sign and magnitude are interpretable. Primarily, marginal effects were calculated to measure the effects of changes in the explanatory variables on the probability of the adoption of precision technologies.

CHAPTER 5

RESULTS

5.0 T-Test

Comparisons between adopters and non-adopters of any PATs are shown in Table 14.

Table 14. Mean significant difference between adopters vs non-adopters of PATs

Dependent Variables	Adopter Mean (N=172)	Non-Adopter Mean (N=27)	Significant Difference
AGE	57.62	64.19	6.55***
CSP	0.23	0.07	-0.16**
CATTLE	0.53	0.44	-0.08
EDUCATION	0.43	0.59	0.15
CROPLANDACRES	2102.26	614.77	-1487.49
SPOUSEOFFFARM	0.54	0.60	0.06
SERVICEISSUE	0.15	0.00	-0.14**
INFOFD	0.79	0.24	-0.55***
TECHACCT	0.71	0.39	-0.31***

Note: ***, **, and * indicate statistical significance at 1%, 5% and 10% levels, respectively.

Ownership of a cattle operation, having a college education, the presence of spousal non-farm income, and farm size were not statistically different. Statistically significant differences between adopters and non-adopters were found for mean producer age, CSP participation, having a service issue due to distance from farm to the service center, use of a farm dealer as their main information source, and using computers for accounting purposes.

Results indicate that producers adopting any one of the top six technologies were about six years younger than those who did not adopt. The mean value (0.03) of the CSP among technology adopters is lower than for non-adopters (0.07), suggesting CSP participation among adopters was lower than for non-adopters. The mean of the servicing issue (0.14) for adopters indicates 14% of adopters have a servicing issue due to distance, which is significantly different from non-adopters who do not have any servicing issues. The mean value those who obtained information from farm dealers (0.78) for adopters indicates 78% of them obtained information from farm dealers, which was significantly higher than the 23% for non-adopters. The mean value of computer usage for accounting-related activities was higher for adopters (0.71) than for non-adopters (0.39), indicating that approximately 71% of adopters used computers for accounting purpose compared to 39% of non-adopters.

5.1 Probit Model

The results of the probit model from equation 16 are shown in Table 15. In a Probit regression, the predicted probabilities of adopting any technology (including auto-steer, variable rate systems, automatic section control/shut-offs, prescription field maps, yield monitors, and GPS guidance systems) were found by using coefficients related to all predictors with a cumulative standard normal distribution function. Interpretation of the coefficient estimates of linear regressions are straightforward, but difficult for a Probit regression. Estimated signs indicate the direction of change, while the marginal effects at the mean and average marginal effect can give a clearer explanation. The probability of adopting precision technology changes with a change in the independent variable (the predictor).

Table 15. Probit Model Parameter Estimates and Marginal Effects

Variables	Coefficient	Standard Error	Marginal Effects
Dependent Variable: Adoption of Precision Agriculture Technologies (APAT)			
AGE	-0.043**	0.0181	-0.004**
CSP	0.002	0.495	0.000
CATTLE	-0.014	0.337	-0.001
EDUCATION	-0.724	0.379	-0.080*
CROPLANDACRES	0.000*	0.000	0.000*
SPOUSEOFFFARM	-0.762*	0.384	-0.084*
SERVICEISSUE	-1.533***	0.372	-0.170***
INFOFD	0.893*	0.364	0.099**
TECHACCT	0.982*	0.413	0.109*
CONSTANT	3.936549**	1.353979	

Note: ***, **, and * indicate statistical significance at 1%, 5% and 10% levels, respectively.

The adoption of precision technology is the dependent variable in the Probit model. The two options for the farm operators are whether or not to adopt PATs. Table 15 shows the Probit estimation results. The servicing issue due to the distance problem is highly significant, while CSP participation and ownership of a cattle operation were not found to be significant.

The age coefficient was found to be negative, indicating that an increase in age decreases the probability of PAT adoption. A one-year increase in age is associated with a 0.4% decrease in the probability of PAT adoption. This result is consistent with findings by Banerjee, et al. (2008), which were based on cotton producers in 11 mid-south and southeastern states. Precision technology was limited to the adoption of GPS guidance systems with a light-bar, auto-steer or any other form of GPS guidance systems. Banerjee, et al. (2008) also found that age was negatively related with PAT adoption, namely sensor-based variable rate applicators, prescription map based variable rate applicators, pest scouting and mapping, remote sensing, GPS receiver, soil variability mapping, water table monitoring, harvesting logistics, and yield monitoring.

CSP participation was not found statistically significant, though it had a positive coefficient. The same relationship was reported by Deutz (2018) for the top three precision technologies namely variable rate technologies, GPS guidance systems, and yield monitors in South Dakota.

Ownership of a cattle operation was not found significant, indicating that there is no statistical difference in PAT adoption rates between producers who operate cattle units and those who do not.

The level of education was not found to be significant in this study. A similar result was reported by Banerjee, et al. (2008) who analyzed PAT adoption rates among cotton producers in 11 states using a binary logit model during 2003-04. Education was also not significant in a probit model applied to citrus production in Florida in 2003 (Sevier and Lee, 2004 a).

As the number of acres under PATs increases, the unit cost of installation and operating PATs decreases, which ultimately reduces the per-acre cost of cultivation. That is, in contrast to small farms, large-scale producers can take advantage of economies of scale. Table 15 shows that as the number of cropland acres increases, the probability of PAT adoption increases significantly. Similar results were reported by Banerjee, et al. (2008) who found that farm size positively influenced GPS adoption.

Table 15 also shows that spousal non-farm income inversely impacts PAT adoption decisions. Marginal effects for off-farm income earned by the spouse was -0.08, indicating that producers having spousal non-farm income were 8% less likely to adopt precision technologies than those who do not. Similarly, Deutz (2018) inferred that operators who earned non-farm income had lower PAT adoption rates.

Servicing issues due to distance problems negatively impacted the decision of adopting precision technology among the respondents. The marginal effect of servicing issues due to distance was -0.17, indicating that producers having servicing concerns due to distance were 17% less likely to adopt precision technologies than those who did not have such concerns.

Knowledge about modern technology is vital to increasing farm productivity. Producers use different Information and Communication Technology (ICT) tools and information sources to carry out their operations. Most producers used implement dealers as their most important information source. Table 15 suggests that farmers who relied on implement dealers as a major information source were more likely to adopt precision technologies than those who utilized other sources of information. The marginal effect of using farm dealers as information source was 0.09, signifying that producers using implement dealers as information source were 9% more likely to adopt precision technologies than those who did not use implement dealers as an information source.

Computers are an increasingly necessary tool for maintaining farm financial records. Using computers for accounting purposes positively influenced the adoption decision of precision technologies among the respondents. The marginal effect of using computers for accounting purposes was 0.10, indicating that producers using computers for accounting purposes were 10% more likely to adopt precision technologies than those who did not. These findings are in line with those of Banerjee, et al. (2008) who also found that the use of computers in farm management was positively related to PAT adoption.

5.2 Count Model

To estimate factors determining the intensity of PAT adoption, the Poisson regression model (count model) was conducted. Results from the Poisson regression with average marginal effects are presented in Table 16. The total bundle of precision technologies was the response variable in the count (Poisson) model and it accounted for the total number of technologies adopted by each producer. Factors included in the analysis were producer age, receipt of government subsidies such as those associated with CSP, cattle operation ownership, education level, cropland acreage, spousal non-farm income earnings, servicing issues due to distance, information from farm dealer and use of computers for accounting purposes.

Table 16. Parameter Estimates and Marginal Effects from the Poisson Model

Independent Variables	Coefficient	Standard Error	Marginal Effects
Dependent Variable: Precision Technology Bundle Adopted (NUMTECH)			
AGE	-0.009*	0.004	-0.027*
CSP	0.324**	0.093	0.998**
CATTLE	-0.210*	0.084	-0.647*
EDUCATION	-0.029	0.086	-0.090
CROPLANDACRES	0.000*	0.000	0.000*
SPOUSEOFFFARM	-0.249**	0.095	-0.766**
SERVICEISSUE	-0.394***	0.108	-1.214***
INFOFD	0.459***	0.103	1.414***
TECHACCT	0.458***	0.104	1.412***
CONSTANT	1.239***	0.309	

Note: ***, **, and * indicate statistical significance at 1%, 5% and 10% levels, respectively.

Overall, the service issue, using farm implement dealers as their information source, and using computers for accounting purposes were found highly significant, while the level of education was not significant. Producer age, ownership of a cattle operation, farm size, and earnings from spouse’s non-farm income were also significant. The Poisson regression estimate shows that an increase in age – while holding the other variables constant – was associated with a decrease in the usage in the number of PATs. The same relationship was found by Lambert, et al. (2015) for cotton production. Results from Table 16 suggest that an additional year in producer age is associated with 3% reduction in precision technologies adopted among the respondents.

CSP had a positive parameter estimate, meaning that producers enrolled in CSP adopted a more technologies than their counterparts who did not. In addition, producers who enrolled in the CSP adopted more technology bundles than those who did not. The marginal effect suggests that CSP participants adopted a larger number of precision technologies by a factor of 100% compared to non-participants in the CSP. Under this program, the government incentivizes producers enrolled in the program to increase their adoption of precision technologies.

Producers with cattle operations adopted fewer technologies than their counterparts without cattle operations, ceteris paribus. The associated marginal effect was -0.65 indicating that the number of precision technologies was 65% lower than for those without cattle operations. A possible reason is that cattle ownership provides a supplementary income source, which may discourage producers to invest in precision agriculture.

The level of education was not significant. This finding is inconsistent with (Isgin, et al., 2008), who found that a college education had a positive impact on the adoption of precision technologies.

An increase in the size of cropland acres positively influenced the adoption of the total number of precision technologies. With all other factors constant, , a one-acre increase in cropland area is associated with a very small increase in the total number of technologies adopted. This result is consistent with findings by Castle, et al. (2016), who observed that acreage had a positive relationship with a technology adoption index in a study on factors influencing PAT adoption in Nebraska.

Table 16 further shows that the existence of spousal non-farm income significantly reduced the adoption of the total number of precision technologies. In particular, non-farm income generated by a spouse reduced the number of precision technologies adopted by producers by 77% compared to those not having off-farm income by a spouse.

Respondents indicating having servicing issues due to distance significantly reduced the total number of precision technology adoption. The marginal effect of servicing issues due to distance was -1.21, indicating that producers having a servicing issue due to distance reduced the number of adopted technologies by 121% compared to those without. The use of a large number of PATs is likely associated with a high level of reliance on repair services; producers facing service center access difficulties may try to avoid the servicing issue by not adopting additional precision technologies.

Producers who relied on farm implement dealers as their main information source for PATs were more likely to adopt PATs than those who used other information sources. The marginal effect of using farm implement dealers as information sources was 1.41, signifying that producers using farm implement dealers as their main information source for PATs were 141% more likely to adopt PATs than their counterparts who relied on other information sources.

Computer usage for accounting purposes also showed a positive relationship with bundles of PAT adoption. The marginal effect of the use of computers for farm accounting activities was also 1.41, indicating that producers using computers for accounting purposes were 141% more likely to adopt PAT bundles than those who did not.

5.3 Negative Binomial Regression

The negative binomial model follows the maximum likelihood procedure. Over-dispersion is modeled with the default method of mean dispersion. The small p-value of the likelihood ratio test indicates that at least one of the regression coefficients in the model was nonzero. The details of the negative binomial regression results are shown in Table 17.

Table 17. Parameter Estimates and Marginal Effects from the Negative Binomial Model

Variables	Coefficient	Standard Error	Marginal Effects
Dependent Variable: Precision Technology Bundle Adopted (NUMTECH)			
AGE	-0.008	0.007	-0.027
CSP	0.317*	0.171	0.991**
CATTLE	-0.211	0.146	-0.660
EDUCATION	-0.052	0.148	-0.164
CROPLANDACRES	0.000	0.000	0.000
SPOUSEOFFFARM	-0.248	0.169	-0.774
SERVICEISSUE	-0.447**	0.173	-1.397**
INFOFD	0.553***	0.159	1.728***
TECHACCT	0.539***	0.164	1.685***
CONSTANT	1.1248**	0.550	

Note: ***, **, and * indicate statistical significance at 1%, 5% and 10% levels, respectively.

In this negative binomial regression model, the total number of technologies adopted by each participant is the dependent variable and is a count variable. The p-values of the binomial regression result show that CSP participation, having servicing issues because of distance, using farm dealers as an the main information source for PATs, and using computers for accounting activities significantly influence the expected counts of the response variable, while ownership of a cattle operation, having a college education, the number of cropland acres, and having a spouse with non-farm income were not statistically significant.

Age and the number of precision technologies adopted were negatively related, suggesting that older producers may be more resistant to adopting larger numbers of such technologies. This inverse relationship was also found by Paxton, et al. (2010) who utilized a negative binomial model in analyzing PAT adoption among cotton producers in the southern United States in 2005. Castle, et al. (2016) found a similar relationship, based on a Poisson regression for Nebraska producers.

CSP participants generally adopted more PATs than those who did not. The marginal effect indicates that CSP participation was associated with a 99% higher number of precision technologies than for non-participants. This result is not surprising, as producers who sign up for the CSP can choose from a large number of conservation practices, including precision agriculture, to address resource concerns on their operation and meet CSP requirements.

Owning a cattle operation was not a significant determinant of the number of precision technologies, and neither was education. The latter finding contradicts Paxton, et al. (2010) who found that the number of years of formal education received by farm operators was significantly related to the number of adopted precision technologies. Furthermore, the number of cropland acres was also not statistically significant, as was spousal non-farm income.

Having servicing issues due to distance was negatively related to the number of precision technologies. The marginal effect of having servicing issues indicates that producers who had servicing issues due to distance decreased the number of precision technologies adopted by 139% compared to those who did not such problems, holding other explanatory variables constant.

Whether producers relied on farm implement dealers as their major information source was positively related to the number of PATs adopted. The marginal effect for the farm implement dealer variable suggests that using farm dealers as a major information source increased the number of PATs adopted by 172% compared with who did not. This finding suggests that farm implement dealers can play a vital role in the PAT adoption decision.

Computer use for accounting purposes was also positively related to the number of adopted PATs. The marginal effect of using a computer for accounting purposes was 1.68, meaning that PAT numbers adopted among users of computers for accounting purposes were 168% greater than among non-users. Paxton, et al. (2010) also found that use of computers for farm management purposes positively related to precision farming tools.

CHAPTER 6

CONCLUSIONS

6.0 Conclusions and Implications

This thesis aims to identify factors influencing precision agriculture technology adoption decision among agricultural producers in South Dakota. The study considers the adoption of individual technologies as well as technology bundles, because PATs may be adopted piecemeal or in bundles.

T-tests were conducted to determine whether the means of adopters and non-adopters were statistically equal to each other for all factors potentially influencing the use of precision technologies. A Probit model indicated that age, size of the farm, spousal non-farm income, precision technology servicing issues due to distance, use of farm dealers as an information source, and computer usage for accounting purposes are significant determinants of PAT adoption. Among these determinants, age, spousal non-farm income and service issues negatively affect the PAT adoption decision, while cropland acres, using farm implement dealers as an information source, and using computers for accounting purposes each have a positive impact. The count model found that all variables except education were found to have a statistically significant effect on the number of technologies adopted in South Dakota. Age, having a cattle operation, spousal non-farm income, and service issue had a negative effect on the number of PATs adopted, whereas CSP enrollment, size of the farm, use of farm dealer as information sources, and using computers for accounting purpose had a positive impact on the bundle of precision technologies adopted. As an extension of the count model, the negative binomial model confirmed that CSP enrollment, the service access issue, using farm implement dealers as information source, and use of a computer for farm accounting had a significant impact on the bundle of precision farming technologies. Only the service access issue due to distance problems had a negative impact on the number of precision technologies. That is, producers are generally not willing to adopt new PATs if they need to visit long distances for servicing or repairing their equipment. Relying on information from farm implement dealers and using computers for accounting purposes are highly significant and have a positive impact on the number of precision technologies adopted, whereas CSP participation had a relatively small but positive impact on PAT adoption.

In summary, all the models suggest that CSP, farm size, use of farm implement dealers as information source, and use of computers in accounting activities have positive impacts on adoption. Age, owning a cattle operation, the existence of spousal non-farm income, service or repair issues related to distance, and education have negative impacts on precision technology adoption and adoption intensity in South Dakota.

6.1 Recommendations

Factors that influence producers in their PAT adoption decisions may be of interest to policy makers for the purpose of encouraging or ameliorating PAT adoption. Policymakers may also be interested in this study's results for the purpose of promoting wider adoption of PATs among the agricultural producers. The study's findings may also be of interest to PAT manufacturers and retailers as they consider approaches to marketing their products.

6.2 Limitations of the Study

This study has a number of limitations. Similar to other survey-based data, the information provided may not accurately reflect the respondents' true situation or include unanswered questions. In addition, the survey data used in our analysis contained several missing and outlier values. Furthermore, variable selection proved challenging. Agricultural producers' decisions to adopt PATs may depend on several variables but the survey instrument included a limited number of options from which to choose, which could potentially exclude other determinants. Also, the bundle of PATs included only six technologies, but in reality additional combined or stand-alone technologies may be considered for adoption. Some PATs were excluded from the analysis because they are not currently widely employed. A final caveat is that technology-related information and economic conditions can become rapidly dated, so if the same survey were conducted at the current time, the results could well differ from the 2016 survey.

6.3 Directions for Future Research

Current and more expansive data could shed additional light on the determinants of PAT decisions among agricultural producers. Also, time-series analysis would be needed to identify any PAT trends. The current study focused on South Dakota as a Midwestern state. Future work could apply the methodologies developed in this thesis to other Midwestern states. Further studies could also consider alternative conditions and variables for PAT adoptions, which might provide additional insights on the determinants of adoption and might also detect adoption patterns and trends.

An additional consideration for any future study is to include costs, revenues, cash flow, risk, capital subsidies, tax reduction, cuts in interests, credit availability, debt to asset ratio, input losses, nutrient amount, experience, perceived benefit and usefulness, willingness to adopt, size of the family as variables to determine the precision adoption decision and adoption intensity. Remote sensing, crop scouting, geographic information systems (GIS), information management, lightbar, grid soil sampling, crop tissue sampling, and aerial/satellite imagery/ image processing technologies can be considered as precision technologies.

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Appendix: Adoption of Conservation and Precision Agriculture Technologies in South Dakota - Crop Year 2016

Part A: Farm Operation

1. In what county is the majority of the agricultural land you operate (including owned and rented) located?___________________county

2. How far away from your operation base is the furthest parcel of land you operate? ______miles

3. On January 1, 2016, how many acres did this operation: (If none, mark X) None Acres

a. Own? . . . . □

b. Rent or lease from others or use rent free? . . . . □

c. Rent to others? . . . . □

4. For the total acres operated in 2016, how many acres were: None Acres

a. Cropland (Exclude hay acres, land in government programs, and cropland pasture □

b. Pastureland (Include cropland /woodland pasture, other pasture and rangeland) □

c. Hayland (Alfalfa or grass) . . . . □

d. Land in government programs (CRP or other) . . . . □

5. For cropland acres (Question 4a), please indicate the acres and production:

Crop	Acres harvested, if none mark X		Total production
	None	Number of Acres	
Corn for grain			Bu.
Corn for silage			Tons
Soybean			Bu.
Wheat			Bu.
Oats			Bu.
Barley			Bu.
Hay - Alfalfa			Tons
Hay - Other			Tons
Sunflower			lbs.
Other (specify)			

6. Did you own any cattle in 2016? Check (✓□ one box per row.

Cattle type	Own
Beef-Cow Calf	Yes □No □

Beef- Feeders (Dairy or Beef)	Yes □No □
Dairy- Cows or Replacements	Yes □No □

Part B: Conservation Agriculture Practices

7. Do you follow a crop rotation on your farm operations? Check (✓)Yes □No □

a. Please list your typical crop rotation.

____

8. Did you use cover crops in 2016? Check (✓)Yes □No □

9. Did you graze crop residue and/or cover crops in 2016? Check (✓)

a. Crop residue? Yes □ No □ b. Cover crops? Yes □ No □

If you did not use cover crops go to Q11.

10. If you used cover crops in 2016 or before, please indicate the importance of each of the following reasons for adoption. (Check ✓one box per row).

Reason	Not Important	Slightly Important	Moderately Important	Very Important
Improves soil health				
Prevent soil erosion				
Suppress weeds				
Breaks pest and disease cycle				
Improves soil water availability/water conservation				
Increases farm productivity				
Increases farm profitability				
Helps with livestock cropland integration				
Participation in federal programs (specify name)				

11. If you did not use cover crops in 2016, please indicate the importance of each of the following reasons for non-adoption. (Check ✓one box per row).

Reason	Not Important	Slightly Important	Moderately Important	Very Important
Not profitable				
Planting time conflicts with harvest of cash crop				
Uncertain about the environmental benefits				
Uncertain about yield benefits				

Risky investment				
Federal program are unattractive				
Satisfied with the current practices				

12. What was your primary tillage practice for row crops in 2016?

a. No- till Yes □ No □

b. Strip-till Yes □ No □

c. Minimum/Reduced till Yes □ No □

d. Conventional till Yes □ No □

If you did not use no-till or strip till, go to Q 15.

13. If answered Yes to no-till/strip-till in Q12, indicate the importance of each of the following reasons for no-till/strip-till adoption. (Check ✓ one box per row).

Reason	Not Important	Slightly Important	Moderately Important	Very Important
Improves soil quality				
Improves water availability/water conservation				
Environmental stewardship				
Adaptation to climate change				
Increases farm productivity				
Increases farm profitability				
Inadequate labor supply				
Participation in federal programs (specify the name)				

14. How many years have you been using no-till/strip-till in your operation?__years

15. If you did not adopt no-till/strip-till in 2016, have you ever adopted it before? Yes □ No □

16. If you stopped using no-till/strip-till, which year did you stop using it?__________year

17. If you stopped using no-till/strip-till, please indicate the reasons why. (Check ✓ one box per row).

Reason	Not Important	Slightly Important	Moderately Important	Very Important
High cost of equipment				
Federal programs were unattractive				
No improvements in soil quality				
No improvements in water availability				
Lower yields				
Not profitable				
Time constraints				
Satisfied with the current practices				

18. If you do not use no-till/strip-till, please indicate the importance of each of the following reasons for not adopting. (Check ✓ one box per row).

Reason	Not Important	Slightly Important	Moderately Important	Very Important
High cost of equipment				
Uncertain about environmental benefits				
Not profitable				
Time constraints				
Lack of information				
Satisfied with the current practices				
Federal programs are unattractive				

19. If you currently don't use no-till/strip-till, would you consider adoption it in future?
Yes □ No □

20. Do you have/use tile drainage on any of the land you operate? Yes □ No □

21. Did you receive cost share or incentive payments in 2016 for any conservation practices implemented on your farm? Yes □ No □
If yes, for which program? Check one box per row

(a) Conservation Stewardship Program (CSP)Yes □ No □
(b) Environmental Quality Incentive Program (EQIP)Yes □ No □
(c) Comprehensive Nutrient Management (CNM)Yes □ No □
(d) State programs Yes □ No □ Yes □
Other (Please list)__________Yes □ No □

Part C: Precision Agriculture Technology Use

For our study, we define autosteer, variable rate, automatic section control, grid soil sampling, prescription field maps, yield monitor, crop tissue sampling, GPS guidance system, and satellite/aerial imagery as precision agriculture technologies. If you are not using any of these technologies currently, please go to Question 30.

22. Do you use autosteer on your farm operation? Yes □ No □
If yes, indicate for which of the following operations?

Operation	Year of first use	Used by (Mark ✓)			Crops used (Mark ✓)
		You	Consultant	Custom Applicator	Corn Soybean Wheat
Tillage					
Fertilizer					
Planting					
Spraying					
Harvest					

23. Do you use a variable rate system on your farm operation? Yes □ No □
If yes, indicate on which of the following operations?

Practice	Year of first use	Used by (Mark ✓)	Crops used (Mark ✓)

		You	Consultant	Custom Applicator	Corn Soybean Wheat
Planting					
Fertilizer-N					
Fertilizer-P					
Fertilizer-K					

24. Do you use automatic section control/shut-offs? Yes □ No □
If yes, indicate which of the following operations?

Practice	Year of first use	Used by (Mark ✓)			Crops used (Mark ✓)
		You	Consultant	Custom Applicator	
Planting					Corn Soybean Wheat
Spraying					
Dry Fertilizer					
Liquid Fertilizer					

25. Please indicate whether you use any of the following precision technologies on your farm.

Technology	Use Y-Yes N-No	Year of first use	Used by (Mark ✓)		
Grid soil sampling			You	Consultant	Custom Applicator
Prescription field maps					
Crop tissue sampling					
Yield monitor					
Aerial/satellite imagery					
GPS guidance system					

26. If you answered Yes to any precision technology questions above, indicate the importance of each of the following in your adoption decision? Check ✓ one box per row.

Reason	Not Important	Slightly Important	Moderately Important	Very Important
Better use of inputs				
Increase in profits				
Increase in productivity				
Environmental benefits				
Being at the forefront of technology				
Participating in federal or state program				
Purchase of new farm equipment				
Helps to manage production and or price				

risks				

27. If you use any precision technologies, how far do you need to travel to service/repair this equipment?______Miles

28. Do you have any service issue because of distance? Yes □ No □

29. Do you think it will be profitable for you to continue to use precision technologies in the future? Yes □ No □

30. Please complete the following table about information sources for precision agriculture technologies even if you are not using them now or have not used before.

Use	Information source							
Mark ✓ if the source was used	Farm dealer	Crop consultant	SDSU extension	Other farmers	Other family	Trade show	News media	Gov't Agency (e.g. NRCS)

31. Please indicate the importance of the each of the following in your decision to not adopt any of above mentioned precision technologies (Questions 22-25). Check ✓ one box per row.

Reason	Not Important	Slightly Important	Moderately Important	Very Important
Not profitable				
Uncertain profits				
Complex technology				
High costs of equipment				
Risky investment				
Uncertain about environmental benefits				
Lack of information				
Federal programs are unattractive				
Satisfied with the current practice				

32. If you currently don't use any precision technologies, would you adopt it in future? Yes □ No□

33. As a crop producer you face financial risks from three primary sources: production, output price, and input cost risk. Please rank these risks 1, 2, or 3, with 1 being a high-risk area of profitability for your farm operation, 2 being a moderate risk, and 3 being a low risk. It is possible that you consider more than one category with the same level of risk. If so, please report it.

Risk type	Rank
Production risk (e.g. drought, weather change, disease/pest outbreak)	
Output price risk (e.g. low price, price fluctuations)	
Input price risk (e.g. rising fertilizer, pesticide, and seed costs)	
Fixed Costs (e.g. rents, machinery, other overhead costs)	

34. During the three-year period 2014 through 2016, indicate the frequency each of the following risk management tools were used by your crop land operation. Check ✓one box per row.

Risk management tools	Never	Sometimes	Always
Crop insurance- Yield protection			

Crop insurance- Revenue protection			
Hedging using futures to manage price risk			
Hedging using options to manage price risk			
Multi-period contracts with elevators for grain delivery			

Part D: Operator characteristics

35. What year were you born? ________________
36. Are you the primary decision maker in your operation? Yes □ No □
If yes, for how many years? _

37. What is the annual gross farm income in your operation? Please check the one that applies to you.

1. Less than $149,999
2. $150,000 - $399,999
3. $400,000 - $749,999

4) $750,000-$1,499,999
5) $1,500,000-$2,499,999
6) $2.5 million or more

38. Do you or your spouse have any off-farm employment?
Operator Yes □ No □ Spouse Yes □ No □

39. What is your level of education? Check ✓one that applies to you.
1. Less than High School/GED □
2. High School/GED □
3. Some College □
4. Occupational/Associates Degree □
5. Bachelor's Degree□
6. Graduate/Professional Degree □

40. Do you use a home computer/iPad/smart phone for the following activities

Computer	Use	I-pad/Smart Phone	Use
Accounting	Yes □ No □	Soil testing	Yes □ No □
Record keeping	Yes □ No □	Field scouting	Yes □ No □
Farm supplies and purchases	Yes □ No □	Rain monitoring	Yes □ No □
Obtain marketing information	Yes □ No □	Market information	Yes □ No □

Do you want a copy of the survey results mailed to you? Yes □ No □
If yes, please provide your contact information. Thank You!