ECONOMIC BENEFITS OF PRECISION AGRICULTURAL TECHNOLOGIES

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Mohsina Jahan

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By

Mohsina Jahan

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

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SUPERVISORY COMMITTEE:

Dr. Cheryl Wachenheim
Chair

Dr. Erik Hanson

Dr. Xin Sun

Approved:

08/15/2022
Date

Dr. William Nganje
Department Chair

ABSTRACT

The purpose of this research was to build a model of profitability that can be used by individual farmers to calculate the net benefits of using precision agricultural technologies on their farms. Three case farms were selected. Partial budgeting analysis is used to calculate the net profit effect of adopting precision agricultural technology bundles. Two scenarios were compared: farms adopting precision agricultural technologies and farms not adopting. Revenues and costs that differ between the two scenarios are included in the model. A six-step process was employed and @Risk was used to account for risk. Results show that adopting PA is profitable for farms with moderate input use variability and this is amplified with higher input prices.

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LIST OF ABBREVIATIONS

GIS……………………………….. Geographical Information Systems

GPS……………………………… Global Positioning Systems

GNSS………………………….. Global Navigation Satellite Systems

PA……………………………..... Precision Agriculture

PAT……………………………… Precision Agricultural Technologies

UAVs…………………………... Unmanned Aerial Vehicles

VRT……………………………… Variable Rate technology

VRTs…………………………… Variable Rate Technologies

YM……………………………... Yield Monitoring Harvesters

Ymap…………………………… Yield Mapping

CHAPTER 1. INTRODUCTION

1.1. Overview

Precision agriculture (PA) refers to a set of technologies that may help reduce input costs and optimize field management practices and yield by providing farmers with detailed spatial information (National Research Council, 1997). According to the International Society for Precision Agriculture (ISPA, 2019), “Precision Agriculture is a management strategy that gathers, processes and analyses temporal, spatial and individual data and combines it with other information to support management decisions according to estimated variability for improved resource use efficiency, productivity, quality, profitability and sustainability of agricultural production”. These benefits result from efficient use of precision agriculture technologies (PAT) such as grid/zone soil mapping, tractor guidance systems, yield monitoring harvesters (YM), yield mapping (Ymap) with Global Positioning Systems (GPS)/ Global Navigation Satellite System (GNSS)[1], Unmanned Aerial Vehicles (UAVs)/drone imagery and variable rate technology (VRT) input application. The use of PA has significantly increased over the last decades, but many farmers are yet to be convinced of the benefits of employing PA on their farms. More research on the economic benefits of PA can give farmers a clear understanding of potential net benefits from adopting PAT given their situation.

1.2. Problem Statement

Precision agriculture has gained an increased importance in the agricultural industry over the past two decades (Schimmelpfennig, 2016; Schimmelpfennig & Lowenberg-DeBoer, 2020).

[1] GNSS is formerly referred to as GPS. The main distinction between GPS and GNSS is that GNSS provides global coverage. Although these terms can be used interchangeably, GNSS is used worldwide. Most of the recent research on precision agriculture uses GNSS instead of GPS.

Considerable research has been conducted in this area and farmers and their advisors are eager to learn about the potential of the technology. Agricultural equipment manufacturers are increasingly producing new and improved technologies to enable farmers practice precision agriculture (Srinivasan, 2006; Wang & Wood, 2021).

Traditionally, a uniform rate of input application was the main strategy for applying inputs on farms (Van Evert et al., 2017). Producers use this method to ensure that plants are getting enough nutrients for their growth and biological needs (Whelan & McBratney, 2000). However, this method has its disadvantages. It may result in over or under application given plant needs and can cause environmental harm from the overapplication of inputs, especially fertilizers and pesticides, and other inorganic chemicals (Bongiovanni & Lowenberg-DeBoer, 2004; Roberts et al., 2000). Before mechanized agriculture, farmers were aware that soil attributes and other agroecological variables are not uniformly distributed across fields and seasons (Bullock et al., 2002; Wang & Wood, 2021). However, due to the unavailability of appropriate technologies, they were not able to use this knowledge to effectively optimize their use of agricultural inputs, especially on large-scale farms (Wang & Wood, 2021).

Precision agriculture, which manages yield potential and within field variability caused by heterogeneity in soil physiochemical properties, could reduce the problems associated with inefficient application or overapplication of inputs and environmental deterioration (Carrer et al., 2022; Finco et al., 2021; Kolady & Van Der Sluis, 2021; Lambert et al. 2015, Lowenberg-DeBoer, 2018; Tey & Brindal, 2012, Van Evert et al., 2017). It can contribute to the long-term sustainability of agriculture through more tailored input application that reduce losses from excess applications and due to nutrient imbalances (Bongiovanni & Lowenberg-Deboer, 2004; Nawar et al., 2017). Understanding soil variability and site-specific management zones enables sustainable resource utilization and crop yield maximization (Srinivasan et al., 2022). Soil and crop variability data also help to reduce costs, increase the efficiency of resource use, and mitigate the environmental impacts (ISPA, 2019; Tey and Brindal, 2012).

PA has considerable potential where input costs are high, inputs are applied at variable rates, high value crops are grown, field variability is high, and environmental deterioration needs to be mitigated (Cowan, 2000; DeLay & Comstock, 2021; Van Evert et al., 2017). Farmers are interested in using PA to improve on-farm profits and reduce impact on the environment (Carrer et al, 2022; DeLay & Comstock, 2021; Van Evert et al., 2017). Applications based on PA technologies are proving to be increasingly important in addressing global market demands for increased agricultural productivity while also promoting environmental sustainability and the green economy (Finco et al., 2021).

The benefits of PA depend on many factors such as region, type of crops grown, soil variability and farm sizes (Van Evert et al., 2017; Schimmelpfennig & Lowenberg-DeBoer, 2020). Although some research has been conducted on the overall economic benefits of PAT, many farmers are yet to be convinced of its profitability. More research is needed on the economic viability of PA based on soil variability and other farm characteristics so that farmers can make informed choices about its adoption. This paper will focus on analyzing how PA can reduce input costs and increase farm profits by efficiently managing agricultural inputs including fertilizers and seed by using technologies such as grid/zone soil sampling, zone mapping, and variable rate technologies (VRTs).

1.3. Objectives

The existing literature largely focuses on adoption rates and profits associated with adopting PAT for different farm sizes, crops, and regions. Much research is generalized across farms, and therefore does not provide individual farmers with a clear understanding of the potential profitability of PAT for use on their unique farms. There is also a gap in the literature on the economic benefits of adopting PAT based on soil variability and individual farm characteristics.

This study will look at the effect of adopting PAT (soil sampling, zone mapping, VRTs) on the profitability of particular farms and develop a simple model to calculate profitability that can be applied to individual farm situations.

1.4. Procedures

In this paper, a model was developed to measure the economic benefits of adopting PA technologies. This model will help farmers finding the profits associated with adopting PA given their unique farm characteristics. Two scenarios were developed in a Microsoft Excel spreadsheet: farms adopting PA and farms not adopting PA. Fertilizer price data used for this model is collected from the DTN ProphetX application. Corn seed price data is collected from North Dakota State University (NDSU) projected crop budgets. Input recommendations and yield goals came from AgVeris, Inc., Casselton, North Dakota. Three case farms were used for the analysis.

The Monte Carlo feature in @Risk is used in this model. @Risk is a risk management tool used as a Microsoft Excel add-in feature. @Risk runs repetitions of the model based on stochastic parameters. The stochastic parameters in this paper include corn and fertilizer prices. Numerous scenarios are examined for each of the variables. Sensitivity analysis is used to gain a better understanding of the outputs of the model. The model will be discussed in greater detail in subsequent chapters.

1.5. Organization

Chapter two describes the literature review. It includes consideration of the literature on adoption rates of PA, factors affecting PA adoption, the rate of PA adoption based on farm characteristics, the economics of adopting PA, and the challenges of PA.

The third chapter presents and explains the empirical model used in this paper. It includes an explanation of the model and input variables, steps in the analysis, @Risk functions, input distributions, and sources of data. Chapter four explains the results in detail which includes the static results, @Risk profit distributions, and sensitivity analysis. Lastly, chapter five provides the key research findings, recommendations, limitations of the study, and opportunities for future research in this area.

CHAPTER 2. LITERATURE REVIEW

2.1. Overview

This section highlights studies related to the objective of the study. Section 2.2 presents research related to the background and adoption rates of PAT. Section 2.3 shows the factors that influenced the adoption of PA. The adoption of PA based on farm characteristics and the economics of adopting PAT are presented in sections 2.4 and 2.5, respectively. Section 2.6 reveals the different challenges of adopting PA.

2.2. Adoption Rates of Precision Agriculture Technologies

Precision agriculture began in the early 1980s with trailblazers, and it is going through evolutionary phases like most other technology-oriented industries, but at a relatively faster pace (Russo, 2014). The commercial application of PAT started in the mid to late 1990s and continues to expand (Bullock et al., 2002; Fountas et al., 2005; Gebbers & Adamchuk, 2010; Griffin & Lowenberg-DeBoer, 2005; Griffin & Yeager, 2018; Kitchen et al., 2002; Lambert et al., 2015; Lowenberg-DeBoer, 2000; McBride & Daberkow, 2003; Popp et al., 2002; Sonka & Cheng, 2015). Precision agricultural practices were introduced to manage agricultural inputs efficiently and reduce environmental deterioration (Schimmelpfennig & Ebel, 2011).

Precision agriculture adoption was first reported in the Corn Belt. It helped to reduce production costs and increase corn, wheat, and soybean yields (Rains & Thomas, 2009). In fact, many PAT were first adopted by U.S. field crop farmers (Lowenberg-DeBoer & Erickson, 2019) and PA adoption patterns in the US have been an indicator of how these technologies will be accepted worldwide. Recently, technologies that are most popular and widely used are Geographical Information Systems (GIS), GPS maps/GNSS, grid/zone soil sampling, YM, Ymap, UAVs/drone imagery, and VRTs (Erickson & Lowenberg-DeBoer, 2020; 2021; Rains & Thomas, 2009; Schimmelpfennig, 2016; Torrez et al., 2016; Zhou et al., 2017).

Various scholars have investigated adoption rates of PAT in the United States (Erickson & Lowenberg-DeBoer, 2020; Schimmelpfennig, 2016; Torrez et al., 2016; Zhou et al., 2017). A 2021 survey of agricultural retailers by Erickson and Lowenberg-DeBoer (2020) showed the current state of precision farming technology adoption from the dealers' perspective. This survey was started in 1997, so it shows the historical perspective of the development and adoption of precision farming technology over time and projects future challenges and opportunities. Dealers report that the availability of service offerings increased drastically from 2008 to 2019, and again from 2019 to 2021. Two-thirds of the dealers in the 2019 dealership survey reported offering field mapping with GIS, GPS guidance with auto control, GPS-enabled sprayer boom, grid or zone soil sampling, satellite, and aerial imagery, VRT lime application, and VRT fertilizer application. According to the 2021 dealership survey, 88% of dealers offer grid or zone soil sampling and VRT fertilizer application, and 44% offer UAVs/drone imagery. Surprisingly, UAVs/drone imagery was not offered in 2008 when the survey was conducted but is forecasted to be offered by 65% of dealers in 2024.

When surveys are conducted from the farmer's perspective, these figures vary slightly. Schimmelpfennig and Ebel (2011) used the United States Department of Agriculture's (USDA) Agricultural Resource Management Survey (ARMS) data to examine the adoption trends of four information technologies: YM, guidance systems, VRTs, and GPS maps, in the production of major field crops. Analyzing the past ten years of ARMS data, the results showed that farmers were using YM on over 40% of U.S. grain crop acres, while GPS maps were used by only a few producers. Adoption rates were lower a decade ago, but they have been increasing significantly over the past few years. Schimmelpfennig (2016) used ARMS data conducted for corn in 2010 and showed that only 12% of small farms (less than 600 acres) reported using at least one PA technology, while large farms (more than 3,800 acres) reported adoption rates of 80%, 84%, and 40% for GPS soil/Ymap, guidance systems, and VRTs, respectively. The ARMS data for winter wheat (2017), corn (2016), and soybeans (2012) also showed that the VRT seeding and pesticide application technologies for these crops were growing rapidly. Using survey data consisting of 198 farm operators in eastern South Dakota, Kolady et al. (2021) found that the adoption rates of YM, GPS guidance, and automatic section control systems were over 50 percent. According to Schimmelpfennig and Lowenberg-DeBoer (2020), guidance systems appeared on 40-60% of planted acres, GPS soil mapping on 15-25% of planted acres, and VRT fertilization on 10-30% of planted acres for major U.S. field crops.

2.3. Factors Affecting the Adoption of Precision Agriculture

There are several factors that affect the adoption rates of PAT. Larkin et al. (2005) demonstrated that farmers with a higher level of education are more likely to believe that PA is important, as is input reduction. Farmers with larger farms or higher yields, as well as those who use personal computers, are more likely to believe that PA can improve the environment. According to Schimmelpfennig & Ebel (2016), education is an important determinant in the adoption of PAT as the sophistication of PA increases. Adoption of PAT is higher when farming is the primary occupation of the farm operators, or the farms are organized as corporations, estates, or trusts (Schimmelpfennig, 2016). The age of the operators also dictates the adoption rate of PAT. Adopting farms of PAT have younger operators than those of nonadopting farms (Dhoubhadel, 2020). According to Schimmelpfennig (2016), concerns about data privacy and security may further influence the adoption of various combinations of PA tools.

Some other important factors that influence PA adoption rate are yield goals and whether irrigation and crop rotation are practiced. Analyzing 2010 ARMS data, Schimmelpfennig (2016) found that U.S. corn farmers practicing crop rotation had higher adoption rates of GPS soil/Ymap, guidance systems, and VRTs than farmers not rotating crops. Irrigated corn acres use GPS mapping and guidance systems more than non-irrigated corn acres. Irrigated acres that are also no-till benefit from even more guidance and VRTs. Farmers with higher yield goals (over 180 bushels per acre) adopt GPS soil/yield mapping, guidance systems, and VRTs at nearly double the rate of farmers with yield goals of 140 to 180 bushels per acre. In contrast to this, a higher adoption rate of guidance systems was found on North Dakota farms with low yield goals but farm sizes exceeding 2000 acres. Farm size can be influenced by a variety of factors, which may also influence PA adoption. The adoption rates of PA were higher in the Corn Belt States than the national average, but North Dakota's rate is even higher.

2.4. Precision Agriculture Adoption Based on Farm Characteristics

Adoption of PA depends on many factors such as farm size (Schimmelpfennig, 2016; Schimmelpfennig & Lowenberg-DeBoer, 2020), type of crops grown (Schimmelpfennig & Lowenberg-DeBoer, 2020), soil variability (Schimmelpfennig, 2016; Schimmelpfennig & Lowenberg-DeBoer, 2020), and region (Schimmelpfennig & Lowenberg-DeBoer, 2020). Many researchers agree that adoption rates have increased over the last two decades and that adoption is higher among larger farms (Schimmelpfennig, 2016; Schimmelpfennig & Lowenberg-DeBoer, 2020). Technology that improves farm profits often takes a long time to get used to because of the unique characteristics of each farm and how much learning is needed to use new technology with old practices. Agriculture in countries with longtime PA experience was found to have a wide range of factors that influenced the adoption of PA technologies, including input use and output level, as well as farm characteristics (Tey and Brindal, 2012). Dhoubhadel (2020) found that farms adopting PAT have a greater average farm size, proportion of cropland, and major crop yield than farms without any PAT, but they have a lower proportion of owned land, and their operators are younger. However, these characteristics of the PA adopting farms can be influenced by some other factors which may also influence PA adoption.

Analyzing nationally representative data from the 2010 ARMS, Schimmelpfennig (2016) found that YM was used on nearly half of the corn farms, whereas Ymap, which uses data from YM, was used on only 25 percent of the corn farms. The second most adopted PAT were guidance systems which were used on 29% of corn farms. By 2010, GPS soil mapping was used on 19 percent of corn farms, as was VRTs. PA technologies have been used on a larger share of corn acres than corn farms, which suggests that bigger farms are more likely to use these technologies. The difference in farm and acreage share is especially large for guidance systems, with 29 percent versus 54 percent, respectively. VRT adoption seemed to depend more on farm size than any other technology, but farm size can also be influenced by many other factors which can affect PA adoption. Adoption of VRTs may also depend on soil and yield variability.

Schimmelpfennig and Lowenberg-DeBoer (2020) studied PA adoption trends for three different crops: winter wheat, corn, and soybeans. The highest adoption of yield and soil mapping was found in the Midwest, where average corn farm sizes are larger, while guidance and VRT seeding are heavily used in the western Midwest. Variable rate fertilization applications were used on one-fifth of planted corn acres in the western Midwest, Midwest, and South regions. The highest adoption rate was found for guidance systems. They are used on 70% of farms growing at least 1,000 acres of corn nationwide. Variable rate pesticide applications were highest in the south, where pest pressures are usually higher. The Midwest showed the highest soil variability and the highest adoption of soil sampling, Ymap, remote sensing, and VRT fertilizer applications.

2.5. Economics of Precision Agriculture

Previous research has considered the economics of adopting PAT (Lambert et al., 2004; Schimmelpfennig, 2016; 2018; Schimmelpfennig & Ebel, 2016; Shockley et al., 2011; Shockley et al., 2012; Smith et al., 2013). Results have been mixed with respect to the impact of these technologies on farm profits. Schimmelpfenning (2016) reported that the adoption of GPS soil and yield mapping, guidance systems, or VRTs led to a positive but small increase (1.1% to 2.8%) in net return and operating profits for corn, and Schimmelpfenning (2018) found almost similar results with a small increase (1.1% to 1.8%) in operating profit for soybeans. According to Thompson et al. (2019), increases in financial returns from the adoption of PA come from two sources: reduced production costs and increased yields. Previously, PA focused on reducing costs through reduced input usage. As technologies have advanced, a greater emphasis has been placed on yield benefits through the more customized use of inputs, with the availability of variable rate input applications.

The USDA ARMS survey provides the most comprehensive data on PA adoption in the United States. The Economic Research Service (ERS) and the National Agricultural Statistics Service (NASS) work together to conduct the survey. Since 1996, the ARMS Survey has been conducting face-to-face interviews with American farmers to gather information on their farming practices and resource use. Schimmelpfennig and Ebel (2016) used USDA's ARMS data to find the cost savings from the adoption of PAT. The results reveal that the adoption of PAT has a negative relationship with production costs. Most of the PA combinations, including YM, Ymap, GPS, soil sampling, and guidance systems, show some cost savings. The largest average variable costs savings ($25.01/acre) was found from the combination of YM and Ymap. Adding VRT to this combination does not bring any further cost reduction, which validates the lower adoption rate of VRT, although some farmers find additional cost savings from VRT. In any scenario when VRT is not being employed, the combination of YM and Ymap alone can save costs for U.S. corn production. However, adding VRT with soil mapping and YM brings additional cost reductions. This scenario shows an increase in cost savings from $13.45/acre (the lowest variable cost reduction among all combinations prior to adding VRT) to $20.56/acre relative to the prior combinations. Schimmelpfennig and Ebel (2016) hypothesized that the inconsistency in cost savings associated with VRT is because it may result in increased input costs in some cases where increased input use can lead to an increase in output and profits.

Schimmelpfennig (2016) compared input costs (fertilizer, pesticide, seed, and fuel) among adopters and nonadopters of PAT (YM, Ymap, soil data mapping, guidance systems, and VRTs) both individually and in six combinations. The author found that PA adopters have a lower input cost in these variable cost categories compared to nonadopters.

According to Dhoubhadel (2020), non-adopting farms of PAT had the lowest average net returns compared to those farms that had one or more PAT without consideration of the relative farm characteristics. Variability of net returns is also relatively higher for non-adopting farms than for farms with two or more technologies. A simple comparison of whether they adopted PAT or not was used to observe the differences in net returns without controlling for the farm characteristics influencing adoption decisions. Schimmelpfennig (2016) said that it can be misleading to simply compare the profit of farmers who use PA technologies with those who don't. Some factors that affect profit, like the size of the farm or managerial sophistication, can also affect whether a farmer adopts the technology. Dhoubhadel (2020) also studied the profit potential of different PAT. The author found that grid soil sampling technology helped farms increase net returns by an average of $53/acre over farms with no PA technology. A combination of technologies was also tested to see their profit potential, which shows that a combination of YM with a grid soil sampling technology is likely to increase net returns by $53/acre. The most notable finding is that any combination of technologies that includes grid soil sampling can positively contribute to the net returns of the farm.

DeLay et al. (2020) provided more insight on issues of PA data analysis and utilization and how they contribute to the profitability of the farms. A 2019 survey of 800 commercial farmers by Purdue's Center for Commercial Agriculture showed that a larger percentage of farmers with 2000 acres or more collected soil samples (80%), YM (85%), and imagery (50%) data. This data influences fertilizer, seeding rate, and drainage decisions. According to survey data, 72% of the respondents reported getting positive yield benefits from data-driven seeding rate decisions, 81% from fertilizer decisions, and 85% from drainage decisions. Data gathered from all three sources yielded better results than if only one data stream is used.

Several factors influenced data collection, including the size of the farm, the age of the farm operators, and the educational attainment of the operators. Large farms are the most likely to collect data, which is in line with previous findings. However, many other factors can also influence the size of the farm, which may influence this data collection process. Farms with younger operators and higher educational levels are more likely to collect farm data. Many farm operators are not experts in collecting and analyzing data collected from PA machinery. So, they subscribe to specialized companies that help them manage their data. According to DeLay et al. (2020), 47% of farms use one or more data software services to manage their data, and this number is even higher (63%) for farms with 5000 acres or more. Over 70% of farmers share their data with an outside service provider, and their seeding and fertility decisions are also highly influenced by the data.

2.6. Challenges of Precision Agriculture

Even though the benefits of PA are widely recognized, its application remains constrained. As a result, the adoption of PAT has encountered additional challenges, including increased application or management costs, investment in new equipment, training of employees for technology use, and uncertainty among the farming community (Finco et al., 2021; Schimmelpfennig, 2016). Adoption of PAT inevitably results in increased capital expenditures on machinery and equipment due to the capital-intensive nature of these technologies. Additionally, machinery has a larger expense base (in comparison to labor costs) and a greater ability to influence overhead costs. This may explain why larger farms adopt PA at a faster rate than smaller farms. Precision agriculture requires investment in equipment, and the capital cost of equipment is spread across more crop-producing acres on larger farms. Farm implements with VRT capabilities have a relatively high capital cost. Therefore, many producers have chosen to hire service providers when selecting VRT, particularly in smaller operations (Schimmelpfennig, 2016). According to Lambert et al. (2004), operator time and effort are a significant cost for VRT and a possible reason for outsourcing the service.

Another big challenge for the adoption of different combinations of PA tools is data privacy and security issues. Some agricultural input companies, including Monsanto and John Deere, provide platforms to farmers that can connect and store data from various technologies in one farmer’s field. Although field data are privacy protected and anonymous, farmers may still be worried because data are linked to the GPS, and they don't have any control over its subsequent use (Schimmelpfennig, 2016).

CHAPTER 3. DATA AND METHODS

3.1. Introduction

The primary goal was to develop a model to help farmers calculate the net benefits of using PA technologies based on their unique farm characteristics. The benefits of PA can be very farm specific. Benefits can vary significantly based on farm size (Dhoubhadel, 2020; Van Evert et al., 2017; Finco et al., 2021; Schimmelpfennig, & Lowenberg-DeBoer, 2020), region (Schimmelpfennig, & Lowenberg-DeBoer, 2020), type of crops grown (Dhoubhadel, 2020; Schimmelpfennig, & Lowenberg-DeBoer, 2020), soil variability (Finco et al., 2021; Fountas et al., 2005; ISPA, 2019; Schimmelpfennig, & Lowenberg-DeBoer, 2020; Srinivasan et al., 2022; Tey & Brindal, 2012), and uncertainty about output and input prices (Finco et al., 2021). Due to the lack of a large dataset that would support attributing net profits to PA adoption and the fact that the net benefits of PA are very farm-specific, the method adopted is appropriate.

3.2. Methods

A partial budgeting model is employed to determine which projects to adopt and which to avoid. The process measures net benefits of a project starting with benefits realized (additional revenues or cost savings) and subtracts additional expenses. In our model, the net benefit of adopting PA technologies including soil sampling, zone mapping and variable rate seed and fertilizer application is assessed. Profit is net return to all costs that are not different between farms with and without precision agricultural technologies employed (Equation 1).

$$\text{Profits} = \text{Revenue} - \text{Costs} \tag{1}$$

The literature supports the use of partial budgeting techniques for measuring the economic benefits of adopting PAT. Soha (2014) used this method to compare the costs and benefits of two sets of farming decisions and determine which one provides the greatest benefit.

Larson et al. (2010) used capital budgeting to develop a decision tool that provides educational information on the ownership and operating expenses of a set of precision agricultural technologies and the required returns to cover the expenses. Other similar methods, treatment-effects models and cost-benefit analysis have also been used. Finco et al. (2021) used cost-benefit analysis to examine the impacts of the introduction of PA technologies on farm profitability and to indicate which course of action should be followed. The treatment-effects model was employed by Schimmelpfennig and Ebel (2016) and Schimmelpfennig (2016). The basic idea behind these methods is to find the net difference in net farm returns caused by the adoption of PA by subtracting the net return of non-adopters (the control group) from the net return of adopters (the treatment group) of PA.

In our analysis, the same case farms are used as both treatment and control groups. First, we calculate the net returns of each farm as non-adopters and then as adopters of PA. For the farms to be considered as PA adopters, all the associated costs that are different from non-adopters (fertilizer, seed, soil sampling, zone mapping, fertilizer recommendation, dry fertilizer application, and hydraulic pump) are added. The difference in net farm returns due to PA adoption is calculated by subtracting the net farm returns of nonadopters from the net farm returns of the adopters of PA. The comparison identifies the associated profit or loss from adoption (Equation 2).

$$\text{Differential Profit} = \text{Profit of PA adopters} - \text{Profit of nonadopters of PA} \qquad (2)$$

The analysis assumes that yield goals are similar whether PA is adopted or not. The focus rather is on the difference in input costs. That is, this analysis assumes an approximately common yield goal; one not dependent on input cost or output price. So, the revenue in both scenarios is similar such that differential profit is just the difference in costs. Although contrary to economic theory, this assumption is not inconsistent with farmer behavior. Anecdotal evidence suggests regional farmers plant so as to maintain or improve on their current yields and to maintain their Actual Production History (APH) yields.

Maintaining or increasing an APH is important. According to American Farm Bureau Insurance Services (AFBIS), INC., APH policies protect farmers from yield losses caused by natural disasters such as drought, excessive moisture, hail, wind, frost, insects, and disease. The producer chooses the percentage of average yield to insure, which ranges from 50 to 75 percent (in some areas to 85 percent). The producer also chooses how much of the predicted price to insure, which can be anywhere from 55% to 100% of the crop price. If the harvested and appraised production is less than the insured yield, the producer gets an indemnity based on the difference. This difference is multiplied by the insured percentage of the price and by the insured share. Thus, federally subsidized crop insurance provides some incentive to apply inputs for yields on marginal acres above that which economist might recommend.

The analysis has several steps. First, budgets are built in Excel under two scenarios: farm not adopting PA and farm adopting PA. The second step of the analysis adds price and risk to the analysis. For the latter, @Risk is used in a six-step process. First, the budget spreadsheet is developed in Microsoft Excel. Second, an @Risk output function is included in the cells containing output formulas. Third, distributions are added to input cells with considered price volatility. Based on the historical input price series, @Risk chooses the best distribution that fits the data automatically using Akaike Information Criterion (AIC). Fourth, the correlation among the variables is put in the input cells. Fifth, determining the number of iterations is set to automatic mode. When automatic iteration is set, @RISK will continue performing iterations until all distributions have achieved convergence. Once this has occurred, @RISK will end the simulation. Iteration is a term that refers to the process of recalculating a model during a simulation; a single simulation consists of numerous iterations. All uncertain variables are sampled once during each iteration based on their probability distributions created by the @RISK distribution function. Iterative sampling produces sampled values and statistics that closely resemble the theoretical distributed values (and statistics) of the input distribution. Lastly, we attribute the simulation to the cell containing the output formula. This subsequently provides a profit distribution.

Calculating profits/losses and comparing two scenarios is the third step of the analysis. Finally, we conduct a sensitivity analysis of the differential profit to changes in input prices.

3.3. Data

Revenues and costs that differ between the two scenarios are included in the model. The primary cost difference is variable inputs of fertilizers and seed. Other costs differing between the scenarios are soil sampling, zone mapping, fertilizer recommendation, dry fertilizer application and hydraulic pump. Input use and yield information for the example farms come from data from three corn farms, one farm in each of Richland (North Dakota), Barnes (North Dakota), and Boone (Eastern Nebraska) counties (table 1). The PA technologies scenarios are estimated using yield goals, seeding rates, and fertilizer application rates for these three farms provided by AgVeris, Inc., Casselton, North Dakota. The firm uses soil sampling and yield data to provide input recommendations for multiple farm zones. For the fertilizer recommendations, fields are divided into five zones and quantity of suggested inputs vary among zones based on the soil variability. The firm uses the national agriculture imagery program (NAIP) and normalized difference vegetation index (NDVI) imagery along with accurate yield data to create five management zones for each field. Each management zone is then soil sampled after harvest, and those results are used to provide fertilizer and seed recommendations for each management zone within a given field. The non-adoption scenarios assume traditional and farm-common yields and application rates for inputs.

Table 1

Case Farm Characteristics

Farm	Location	Size (acres)	Irrigation Type	Soil variability
FARM A	Richland county, ND (South Valley region)	158	Non irrigated	Little to no soil variability or topography
FARM B	Barnes County, ND (Southeast Region)	161	Non irrigated	Significant soil variability with moderate topography
FARM C	Boone county, Eastern Nebraska	125	Irrigated	Moderate soil variability with no topography

Table 2

Sample Fertilizer Recommendations by Zones

CORN	ZONE 1	ZONE 2	ZONE 3	ZONE 4	ZONE 5	WEIGHTED AVERAGE OF 5 ZONES	TRADITIONAL RATE
YIELD GOAL - BUSHEL	120	150	160	180	200	189.07	185
SEED RATE (1000)	24	27	29	31	35	31.6	32
NITROGEN - UREA (LB)	195	215	268	270	295	271	325
PHOSPHORUS - MAP (LB)	0	19	50	100	140	102	100
POTASSIUM - POTASH (LB)	0	0	70	74	75	65	100
SULFUR - AMS (LB)	20	47	51	60	66	58	75
POPUP FERT - 6-24-6 (GAL)	3.0	3.0	4.5	4.5	5.0	4	5.0

Table 2 shows a sample fertilizer recommendation. The first column lists the yield goals and names of different inputs. Yield goal is measured in bushels and seeding rate is in counts. All fertilizers are given in pounds except popup fertilizer which is in gallons. Here, the field is divided into five zones based on soil productivity. Weighted average of five zones is calculated for yield goals and all other inputs. The last column shows the traditional rate of applications that were used before adopting PA. In most cases, yield goals are similar for both PA and traditional fields, but input recommendations are lower for PA. The costs that are different between PA and traditional rate are considered for our analysis. Table 3 shows that soil sampling and dry fertilizer application costs are always higher for PA adopters than non-adopters. On the other hand, zone mapping, fertilizer recommendations, and hydraulic pump costs are only applicable to PA. The source of these rates is Agveris, Inc., Casselton, North Dakota.

Table 3

Cost Differences Between the PA and Traditional Rate (Per Acre)

Costs	PA Rate	Traditional Rate
Soil Sampling costs	2.5	1.25
Zone Mapping costs	3	N/A
Fertilizer Recommendation Costs	6	N/A
Dry Fertilizer Application Costs	10	8
Hydraulic Pump	1	N/A

Historical monthly prices of corn and fertilizers (except sulfur) are collected from the DTN ProphetX application. North Dakota average corn monthly price series from 2010-2020 was used in our analysis. The historical monthly price series starting from 2010 to 2020 was used for nitrogen (Urea), phosphorus (MAP)[2], potash, popup (10-34-0), and UAN[3] 28. The yearly price series of sulfur from 2010-2022 is used (Ron Haugen, Personal communication, May 10th, 2022) due to unavailability of monthly price series. Corn seed price data is collected from NDSU projected crop budgets. We excluded 2021 and 2022 prices from our analysis because price of

[2] Monoammonium Phosphate is referred to as MAP.

[3] Urea Ammonium Nitrate is referred to as UAN.

corn and all fertilizers started to increase sharply from 2021. The graphs below show price volatility in the periods mentioned above.

Figure 1

Historical Corn Price Series

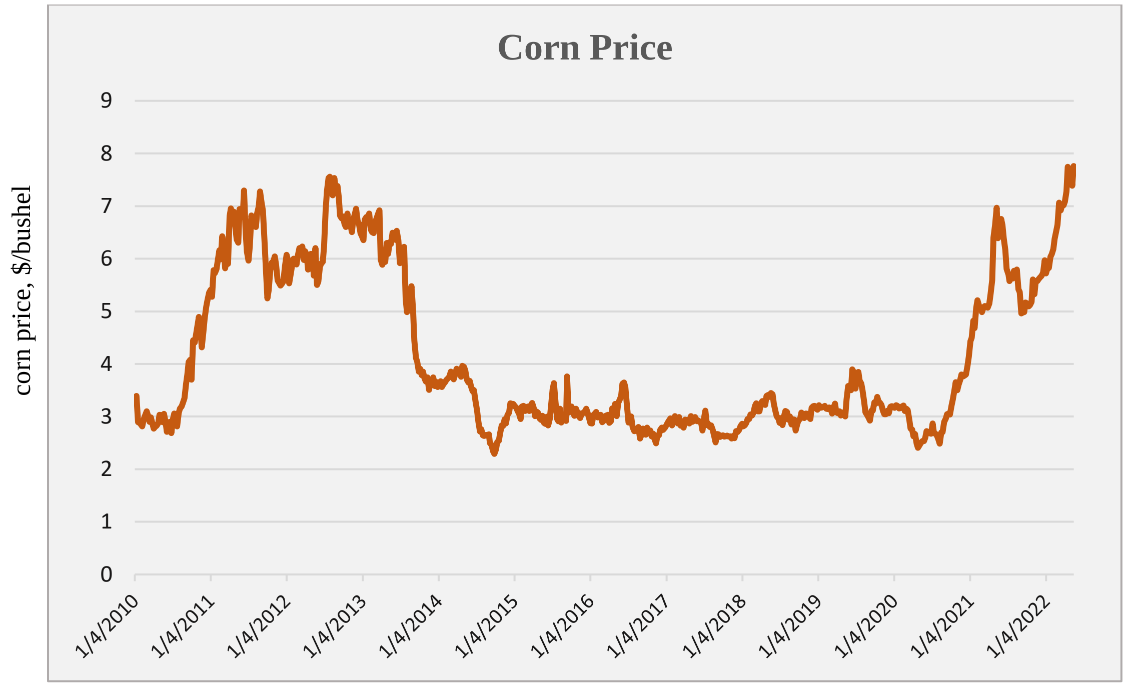


Figure 2

Historical Urea Price Series

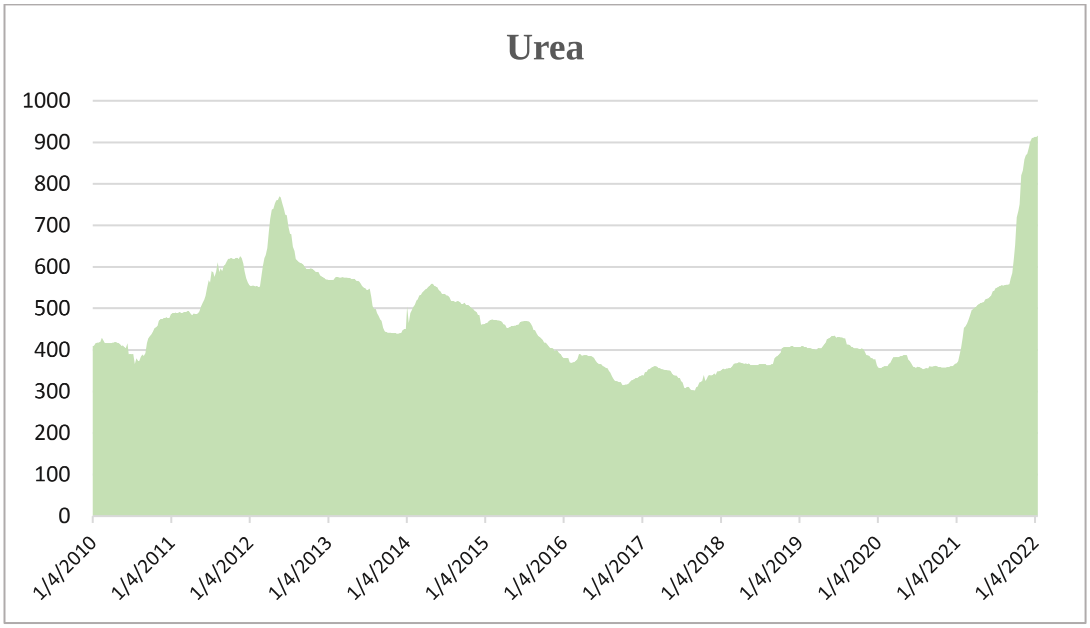


Figure 3

Historical MAP Price Series

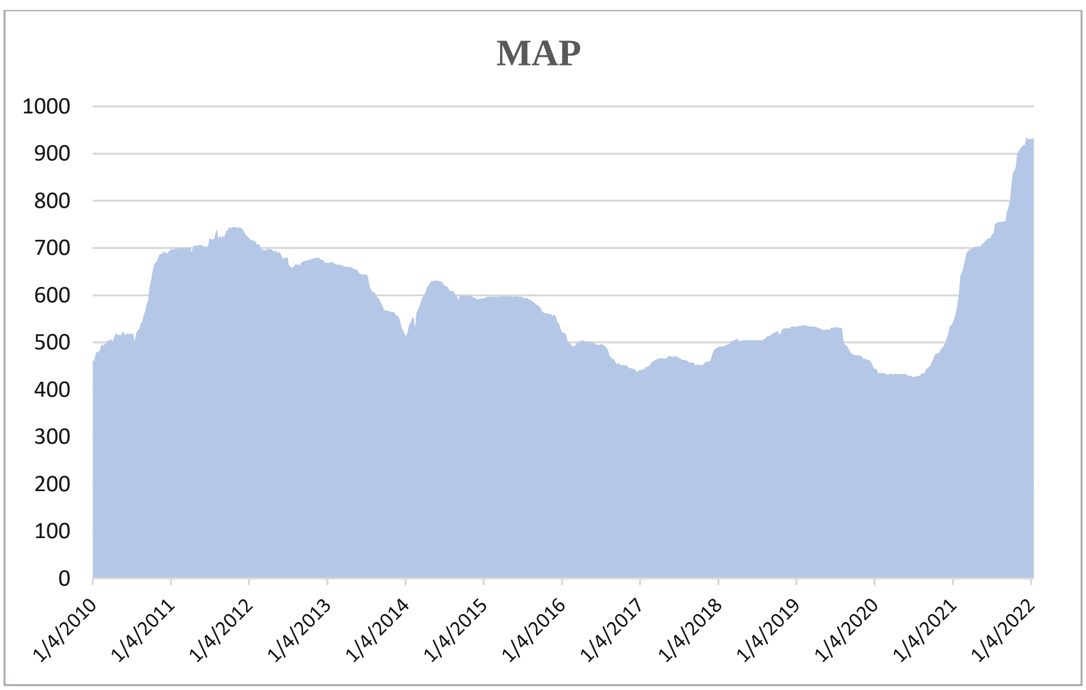
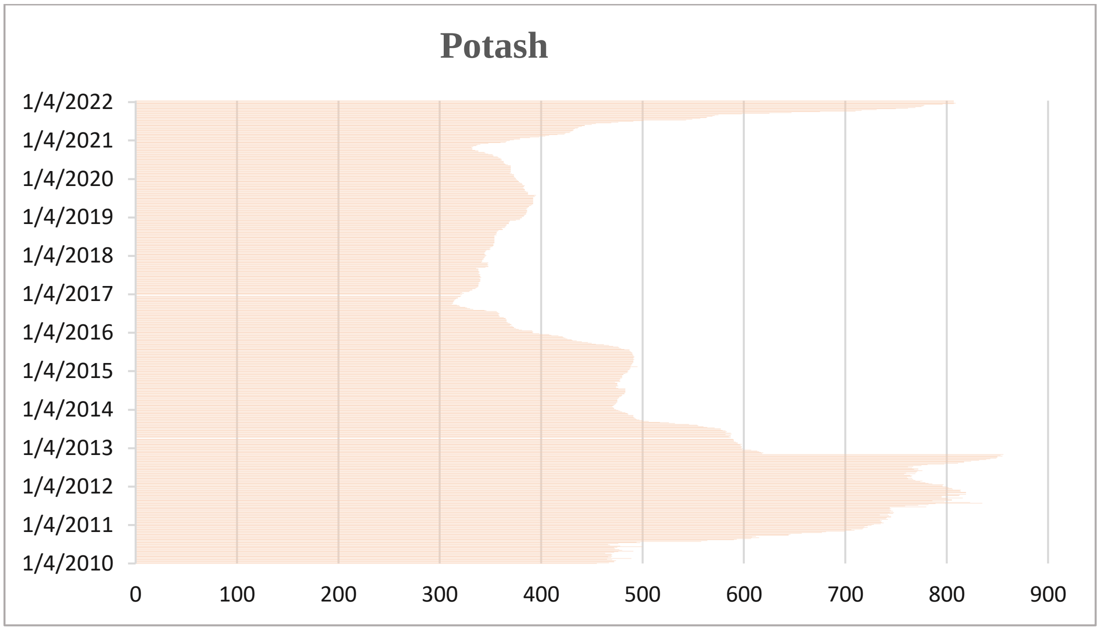


Figure 4

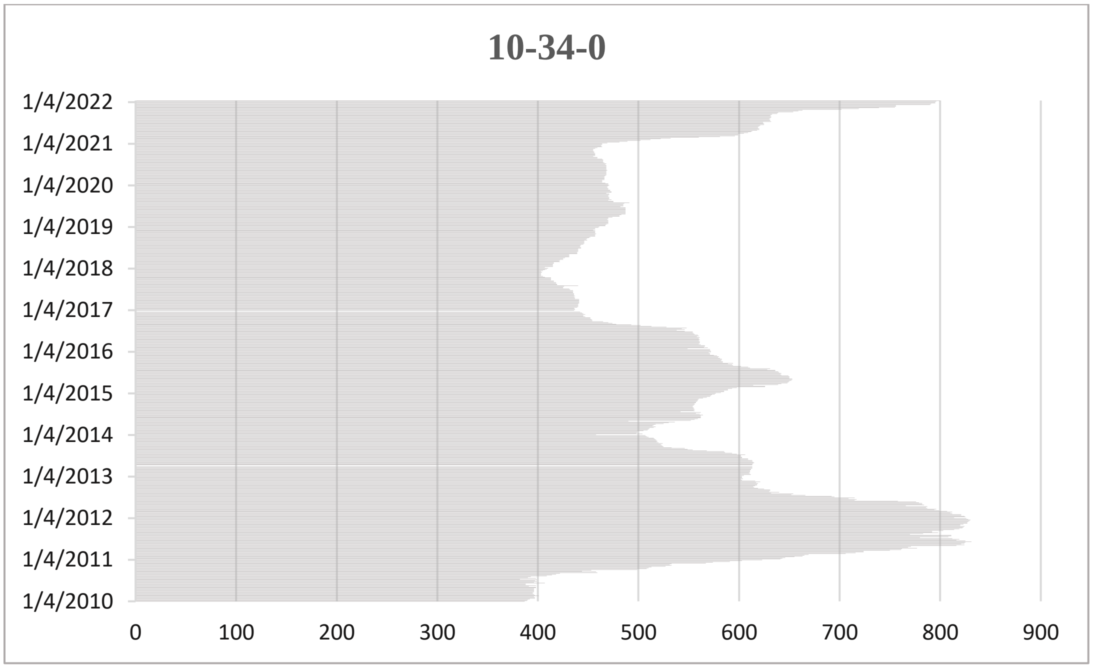
Historical Potash Price Series



potash Price, $/ton

Figure 5

Historical 10-34-0 Price Series



10-34-0 price, $/ton

Figure 6

Historical UAN 28 Price Series

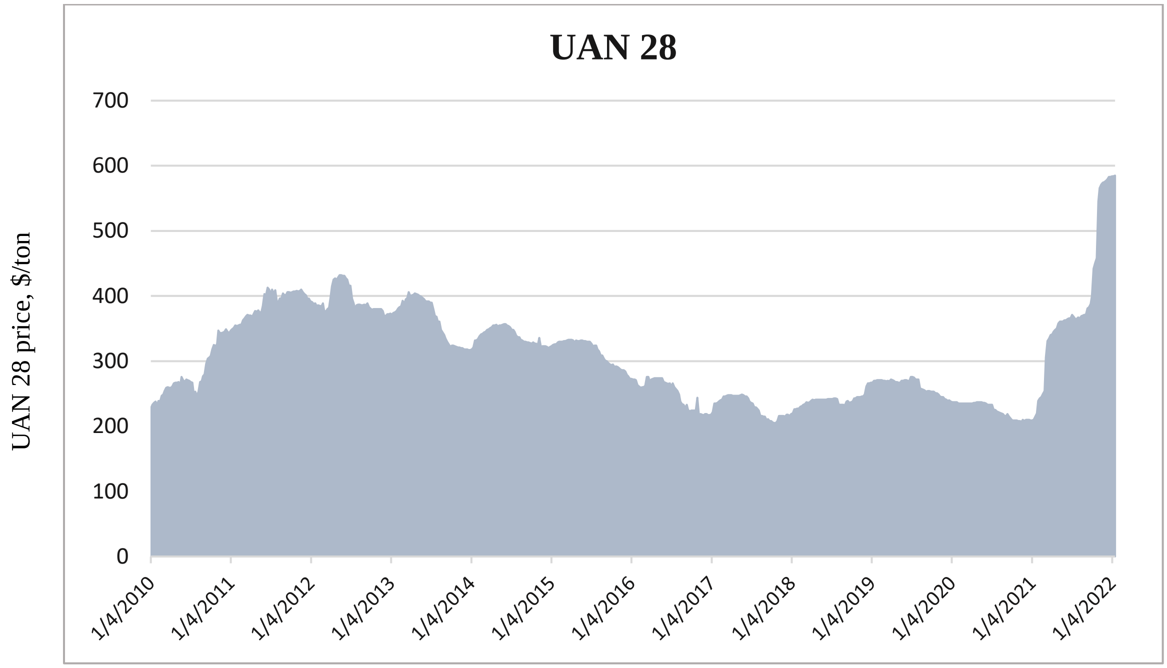
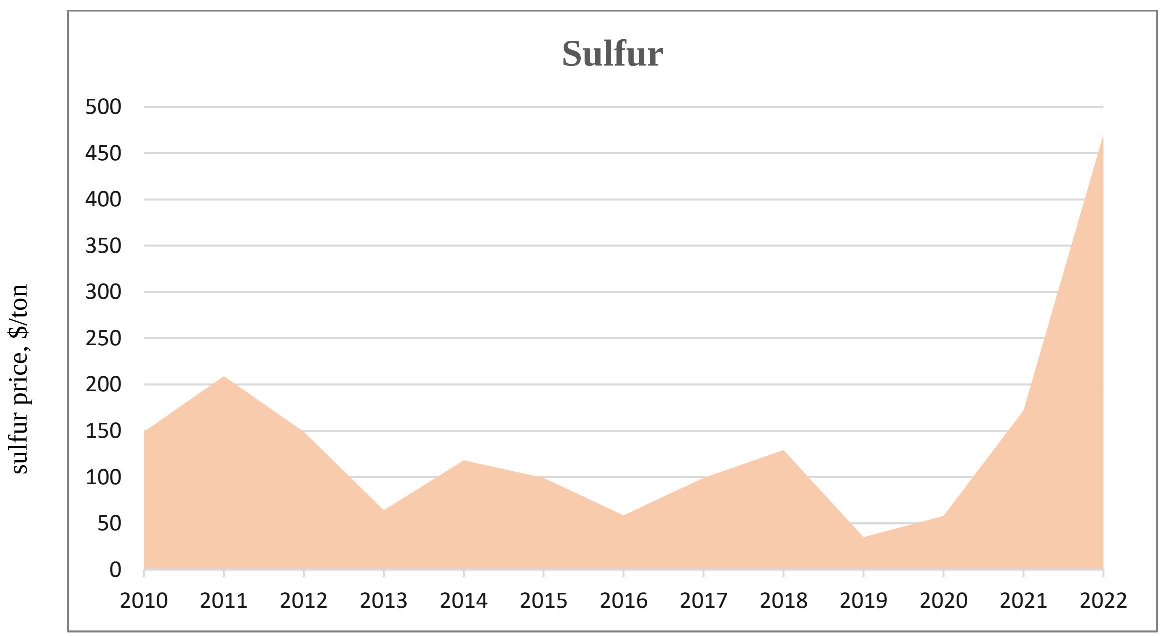


Figure 7

Historical Sulfur Price Series



CHAPTER 4. ANALYSIS AND RESULTS

The objective was to identify the differential profit per acre to identify the net benefit of adopting PAT. Farmers can use this model and plug in their numbers to find out the differential profits for their own farms. Differential profit is the difference between the profit of PA adopters and non-adopters of PA.

4.1. Static Results and Sensitivity Analysis

Table 4 shows static results using input prices from December 2020, when prices began to increase substantially associated with trade policy and COVID-19-related anomalies. The result is annual net profit associated with PA adoption. The differential profit is obtained by subtracting the profit of non-adopters from the adopters of PA.

Table 4

Static Results

	FARM A		FARM B		FARM C	
	PA	Traditional	PA	Traditional	PA	Traditional
Profit*, $/acre	395	371	329	316	653	657
Differential profit, $/acre	23		13		-4	

*Profit per acre is the return to fixed costs, management, and input costs except those noted as different between the adoption and non-adoption scenarios.

Static results show that the differential profit per acre for farm A is $23, whereas for farm B it is $13. Our hypothesis suggests that, because Farm B has more soil variability than Farm A, it would have a higher differential profit per acre. Results show the opposite. The reason behind this is that there is a slight difference in yield goals between the PA and traditional scenarios of both farms. Farm A's PA yield goal is 4 bushels/acre higher than the traditional rate. On the other hand, Farm B's PA yield goal is 2 bushels/acre lower than the traditional rate. The higher yield goal for the PA scenario in farm A brings additional revenue, which increases the differential profit per acre for farm A. If the yield goals for each were the same, the profit differential for Farm B would be higher.

Sensitivity analysis calculates net profit differential using June 2022[4] input prices to compare the change in profits when prices are increased by almost double (table 5). The results show that differential profit is increased by more than double the 2020 static results.

Table 5

Sensitivity Analysis of Profits and Differential Profits

Sensitivity Analysis	FARM A		FARM B		FARM C	
	PA	Traditional	PA	Traditional	PA	Traditional
Profit*, $/acre	489	437	417	379	772	769
Differential profit, $/acre (June 2022 prices)	52		38		3	
Differential profit, $/acre (December 2020 prices)	23		13		-4	

*Profit per acre is the return to fixed costs, management, and input costs except those noted as different between the adoption and non-adoption scenarios.

Figure 8 shows the sensitivity of differential profits to changes in corn seed and all fertilizer prices. The horizontal axis shows the percentage change in the price of seed and fertilizers, whereas the vertical axis shows the associated changes in differential profits for each of the three farms. In the base point, we are using input data from December 2020. Percentages on the horizontal axis show the assumed increase in the prices of both seed and fertilizers. In figure 8, we can see that differential profits for farms A, B, and C in the base point were $23, $13, and -$4 per acre, respectively. When the input prices were increased by 100%, which is similar to 2022 prices, differential profits almost doubled. The figure shows that, when the prices

[4] In 2022, the cost of all fertilizers increased significantly in large part due to supply and logistical challenges associated with the COVID pandemic. In most cases, prices considered are more than double 2020 prices.

of inputs increase, the profits of farms adopting PA increase significantly. Among all three farms, the rate of increase in differential profits per acre with respect to increases in input prices is the highest for farm B. This farm is using some of the more expensive fertilizers. The reduced cost associated with Farm B applying less fertilizer is greater under higher fertilizer prices. Ultimately, higher per unit costs of inputs variable rate applied leads to an increase in profits associated with using PA for Farm B as compared to the other case farms, leading to convergence of the profit differential.

Figure 8

Sensitivity of Differential Profits to Input Price Changes

4.2. Risk Analysis

The @Risk simulation feature was used to develop profit distributions for the three sample farms. Table 6 contains statistical characteristics of the profit distributions. When the price of the inputs is low, the differential profit is at a minimum. This is because there are fewer cost savings associated with applying less inputs. Profit is higher when the price of inputs increases and farmers are using PA to apply fewer inputs, which will lead to greater cost savings. For the static analysis, we used only December 2020 prices. But for the @Risk simulation, input price series starting from 2010 to 2020 are used. This is the reason that the differential profit coming from the simulation can vary from the static results.

Table 6

Differential Profit Statistics from @Risk Sensitivity Analysis

Differential Profit/acre	Farm A	Farm B	Farm C
Minimum	26	10	-3
Maximum	66	29	4
Mean	30	13	-2
Standard deviation	3.1	1.7	.8

Farm A can earn a minimum differential profit of $26/acre and a maximum of $66/acre (table 6). Profit differential is at its minimum at low input prices and at its maximum at high input prices. The mean differential profit for farm A is $30/acre (table 6). There is a 90% probability that the differential profit will be between $27/acre and $35/acre, which is much higher than our static results (figure 9). It is evident that adopting PA is profitable for farm A, not only under a higher price (figure 8), but also in a regular market environment (figure 9).

Figure 9

Differential Profit/acre for Farm A

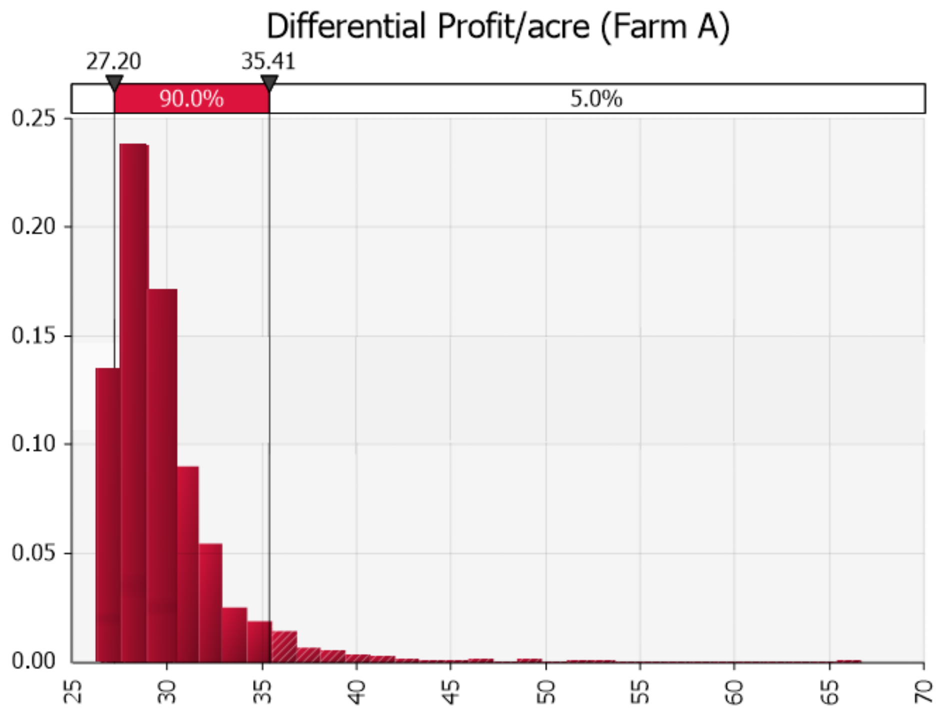
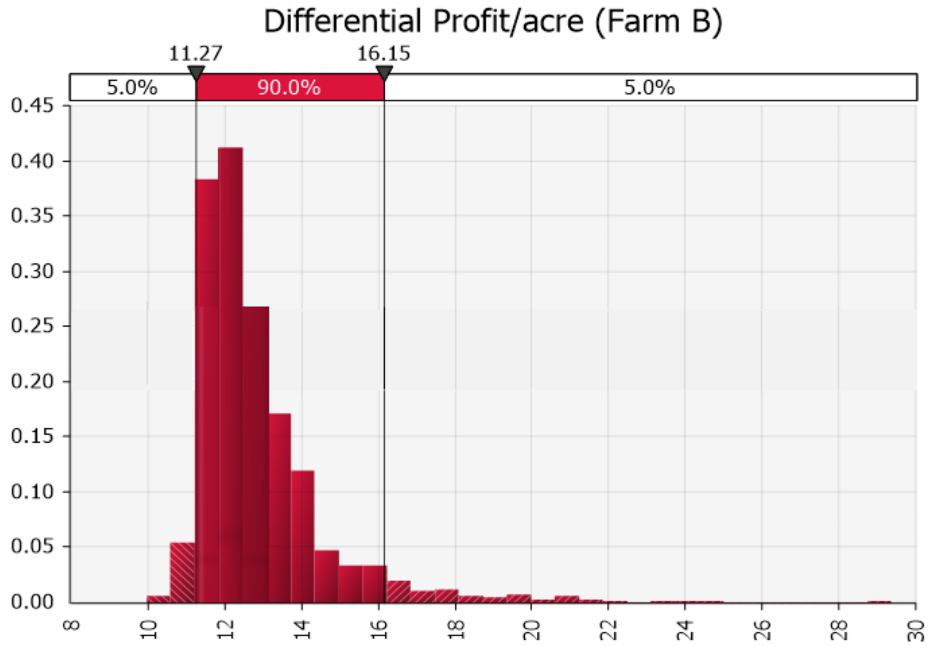


Table 6 shows a differential profit per acre for farm B of between $10 and $29. The mean differential profit is $13/acre. There is a 90% probability that the differential profit will be between $11/acre and $16/acre, which is a little higher than the average static results (figure 10). So, adopting PA for farm B is moderately profitable in a normal market environment. But, when the price of the inputs increases significantly, the rate of increase in differential profit per acre for farm B is higher than for farm A (figure 8). This is expected because farm B is using some more expensive fertilizers. So, with the increase in fertilizer prices, farm B can save more costs by applying fewer inputs according to fertilizer recommendations.

Figure 10

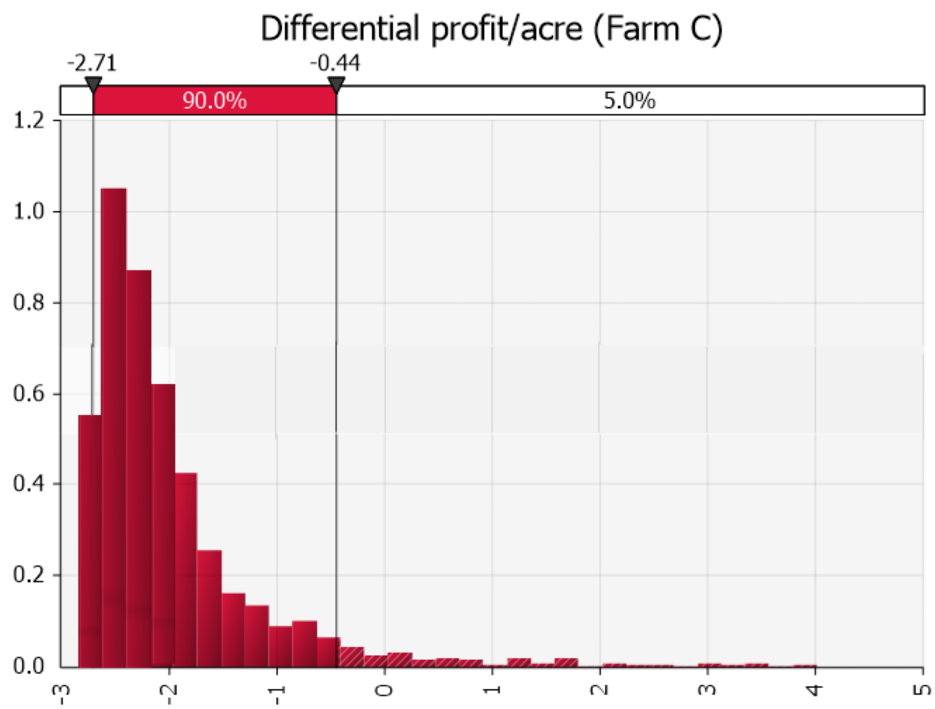
Differential Profit/acre for Farm B



Farm C can earn a minimum differential profit of -$3/acre and a maximum of $4/acre (table 6). The mean differential profit for farm A is -$2/acre. There is a 90% probability that the differential profit per acre will be between -$3/acre and $0/acre, which is higher than our static results (figure 11). Farm C was an irrigated field, and they applied some fertilizer through irrigation to all zones at a flat rate. According to its fertilizer recommendation, there was little to no difference between the PA and the traditional rate of input applications. That is why farm C shows few or no cost savings when adopting PA.

Figure 11

Differential Profit/acre for Farm C



CHAPTER 5. CONCLUSIONS

5.1. Conclusions and Implications

The primary goal of this research was to build a model that farmers can use to calculate the net benefits of adopting PAT based on their unique farm characteristics. Our hypotheses were that adoption of precision agriculture would increase net profit and that an increase in input prices will result in a larger differential profit between farms adopting PA and those not because applying fewer inputs will lead to a greater savings in input costs under higher prices.

Results support the hypothesis, showing that the bundle of technologies including soil sampling, zone mapping, and VRT can be moderately to highly profitable for farms which are variable in terms of soil fertility. The more variable the field, the higher the probability of an increased differential profit per acre. Our analysis shows that adoption of PA is highly profitable for farm A where input use was more variable across the farm. The range of differential profit is between $26 and $66 dollars per acre. The differential profit for farm B is moderate, ranging from $10 to $29 dollars per acre. This farm had less variability but applied some more expensive fertilizers so differential profit grew with increased input prices. Adopting PAT for Farm C did not increase profits with a 90% probability of small but negative differential profits per acre.

5.2. Recommendations

Adopting PA would be moderately to highly profitable for non-irrigating farms based on their soil variability and unique farm characteristics. However, a traditional rate of input application may be more appropriate for irrigated farms as there is not much variability in the input application rate when PA is used and when it is not as irrigated farms are able to control the variability within the fields. So, adopting PA for irrigated fields may introduce only small input cost savings.

The technology bundle (soil sampling, zone mapping, VRT) considered for this research can be suggested to farmers who have a variable field in terms of soil productivity, noting that more field variability will increase the differential profit per acre of the farm. It is important that farmers estimate and use their own soil variability information, prices, and costs associated with adopting precision agriculture in estimating the potential for their farm operation.

5.3. Limitations of the Study

We offer a case study approach to considering the PAT adoption decision. Specific results are therefore limited to the specific case farms considered. Some previous research has used large databases including ARMS to estimate the effect of adoption of PAT bundles on farm profitability. There are notable concerns about this method and authors frequently indicate the limitation that there may be other farm and farmer characteristic factors not included in the model that are correlated with PAT adoption and also affect farm profitability; that is, that attributing the difference in farm profitability simply to PAT adoption may overstate its effect. Examples of such characteristics are management capability or entrepreneurial experience and acumen.

The lack of a large enough data set representing regional farmers, the quick evolution of PAT adoption, and variation in the rate of use of PAT even when adopted made the use of statistical regression to compare profitability of adopters and non-adopters impractical. Further, we recognized the value of developing a model that will help farmers with their adoption decisions in the future. Therefore, we relied on the case study approach. We are using three case farms for our analysis and focused on building a model that can be used by individual farmers to calculate the net benefits of using PAT based on their unique farm characteristics.

Adopting additional farmers farms with a varied degree of soil variability could shed additional light in this area, as would considering additional technologies and technology bundles.

5.4. Directions for Future Research

Future studies on the profitability of adopting PAT can be done with a large dataset and varied types of fields that have adopted PA on their farms. Taking sample farms from different states and including farms producing different types of crops could shed additional light on the profitability of adopting PAT. Farms can vary considerably in terms of the soil variability and their topography. So, more research can be done on the impact of soil variability on the profitability of farms adopting PAT. Additional PAT bundles will also be of value.

REFERENCES

American Farm Bureau Insurance Services (AFBIS), INC. *Actual Production History (APH).* https://www.farmbureausellscropinsurance.com/insurance-plans/mpci/actual-production-history/

Bongiovanni, R., & Lowenberg-DeBoer, J. (2004). Precision agriculture and sustainability. *Precision agriculture*, *5*(4), 359-387. https://doi.org/10.1023/B:PRAG.0000040806.39604.aa

Bullock, D. S., Lowenberg-DeBoer, J., & Swinton, S. M. (2002). Adding value to spatially managed inputs by understanding site-specific yield response. *Agricultural Economics*, *27*(3), 233-245. https://doi.org/10.1111/j.1574-0862.2002.tb00119.x

Carrer, M. J., de Souza Filho, H. M., Vinholis, M. D. M. B., & Mozambani, C. I. (2022). Precision agriculture adoption and technical efficiency: An analysis of sugarcane farms in Brazil. *Technological Forecasting and Social Change*, *177*, 121510. https://doi.org/10.1016/j.techfore.2022.121510

Cowan. (2000). CRS report for Congress: Precision agriculture and site-specific management: Current status and emerging policy issues. https://www.amazon.com/Crs-Report-Congress-Agriculture-Site-Specific/dp/1294255711

DeLay, N., & Comstock, H. (2021). Recent Trends in PA Technology Adoption and Bundling in Corn Production: Implications for Farm Consolidation. *Western Economics Forum,*19(2), 44-57. https://doi.org/10.22004/ag.econ.315935

DeLay, N., Thompson, N., & Mintert, J. (January 23, 2020). Farm data usage in commercial agriculture. *Purdue University Center for commercial agriculture.*

https://ag.purdue.edu/commercialag/home/resource/2020/01/farm-data-usage-in-commercial-agriculture/

Dhoubhadel, S. P., (2020). Precision Agriculture Technologies and Farm Profitability. *Journal of Agricultural and Resource Economics, Western Agricultural Economics Association*, 46(2). https://doi.org/10.22004/ag.econ.303598

DTN ProphetX (2022). Fertilizer National and State Averages. Retrieved on May 18, 2022.

Erickson, B., and Lowenberg-DeBoer, J. (2020). *2020 Precision Agricultural Services Dealership Survey.* Croplife. https://ag.purdue.edu/digital-ag-resources/wp-content/uploads/2020/11/CropLife-Report-2020.pdf

Erickson, B., and Lowenberg-DeBoer, J. (2021). *2021 Precision Agriculture Dealership Survey Confirms a Data Driven Market for Retailers.* Croplife. https://www.croplife.com/management/2021-precision-agriculture-dealership-survey-confirms-a-data-driven-market-for-retailers/

Finco, A., Bucci, G., Belletti, M., & Bentivoglio, D. (2021). The economic results of investing in precision agriculture in durum wheat production: A case study in central Italy. *Agronomy*, *11*(8), 1520. https://doi.org/10.3390/agronomy11081520

Fountas, S., Blackmore, S., Ess, D., Hawkins, S., Blumhoff, G., Lowenberg-Deboer, J., & Sorensen, C. G. (2005). Farmer experience with precision agriculture in Denmark and the US Eastern Corn Belt. *Precision Agriculture, 6*(2), 121-141. https://doi.org/10.1007/s11119-004-1030-z

Gebbers, R., and V.I. Adamchuk. (2010). Precision agriculture and food security. *Science*. 327(5967):828–31. http://dx.doi.org/10.1126/science.1183899

Griffin, T. W., & Lowenberg-DeBoer, J. (2005). Worldwide adoption and profitability of precision agriculture Implications for Brazil. *Revista de Politica Agricola*, *14*(4), 20-37. https://seer.sede.embrapa.br/index.php/RPA/article/view/549

Griffin, T. W., & Yeager, E. A. (2018). Adoption of precision agriculture technology: A duration analysis. In Proceedings of 14th International Conference on Precision Agriculture. Monticello, IL: International Society of Precision Agriculture. https://www.ispag.org/proceedings/?action=abstract&id=5271&title=Adoption+of+Precision+Agriculture+Technology%3A+A+Duration+Analysis&search=years

International Society of Precision Agriculture – ISPA (2019). https://www.ispag.org

Kitchen, N. R., Snyder, C. J., Franzen, D. W., & Wiebold, W. J. (2002). Educational needs of precision agriculture. *Precision agriculture*, *3*(4), 341-351. https://doi.org/10.1023/A:1021588721188

Kolady, D. E., & Van Der Sluis, E. (2021). Adoption Determinants of Precision Agriculture Technologies and Conservation Agriculture: Evidence from South Dakota. *Western Economics Forum*, 19(2), 28-43. https://doi.org/10.22004/ag.econ.315934

Kolady, D. E., Van der Sluis, E., Uddin, M. M., & Deutz, A. P. (2021). Determinants of adoption and adoption intensity of precision agriculture technologies: evidence from South Dakota. *Precision Agriculture*, *22*(3), 689-710. https://doi.org/10.1007/s11119-020-09750-2

Lambert, D. M., Lowenberg-DeBoer, J., Griffin, T. W., Peone, J., Payne, T., & Daberkow, S. G. (2004). *Adoption, profitability, and making better use of precision farming data* (No. 1239-2016-101578). http://dx.doi.org/10.22004/ag.econ.28615

Lambert, D. M., Paudel, K. P., & Larson, J. A. (2015). Bundled Adoption of Precision Agriculture Technologies by Cotton Producers. *Journal of Agricultural and Resource Economics*, *40*(2), 325–345. http://www.jstor.org/stable/44131864

Larkin, S., Perruso, L., Marra, M., Roberts, R., English, B., Larson, J., . . . Martin, S. (2005). Factors Affecting Perceived Improvements in Environmental Quality from Precision Farming. *Journal of Agricultural and Applied Economics, 37*(3), 577-588. https://doi.org/10.1017/S1074070800027097

Larson, J. A., Mooney, D. F., Roberts, R. K., & English, B. C. (2010). A computer decision aid for the cotton precision agriculture investment decision. In *Proceedings of the 10th international conference on precision agriculture.* https://www.ispag.org/proceedings/?action=abstract&id=420&title=A+Computer+Decision+Aid+For+The+Cotton+Precision+Agriculture+Investment+Decision+&search=topics

Lowenberg-DeBoer, J. (2000). Economic analysis of precision farming. *Federal University of Vicosa, Vicosa, Brazil*. http://www.ufrrj.br/institutos/it/deng/varella/Downloads/IT190_principios_em_agricultura_de_precisao/livros/Capitulo_7.pdf

Lowenberg-DeBoer, J. (2018). The economics of precision agriculture. *Precision agriculture for sustainability* (pp. 481-502). Burleigh Dodds Science Publishing.

Lowenberg-DeBoer, J., & Erickson, B. (2019). Setting the record straight on precision agriculture adoption. *Agronomy Journal*, *111*(4), 1552-1569. https://doi.org/10.2134/agronj2018.12.0779

McBride, W. D., & Daberkow, S. G. (2003). Information and the adoption of precision farming technologies. *Journal of Agribusiness*, *21*(345-2016-15210), 21-38. http://dx.doi.org/10.22004/ag.econ.14671

National Research Council. (1997). Precision agriculture in the 21st century: Geospatial and information technologies in crop management. Natl Academy Pr. https://nap.nationalacademies.org/catalog/5491/precision-agriculture-in-the-21st-century-geospatial-and-information-technologies

Nawar, S., Corstanje, R., Halcro, G., Mulla, D., & Mouazen, A. M. (2017). Delineation of soil management zones for variable-rate fertilization: A review. *Advances in agronomy*, *143*, 175-245. https://doi.org/10.1016/bs.agron.2017.01.003

Popp, J., Griffin, T., & Pendergrass, E. (2002). How cooperation may lead to consensus assessing the realities and perceptions of precision farming in your state. *The Journal of the ASFMRA*, 26. https://www.proquest.com/docview/219552736?pq-origsite=gscholar&fromopenview=true

Rains, G. C., & Thomas, D. L. (2009). *Precision farming: An introduction*. The University of Georgia. Bulletin 1186. http://hdl.handle.net/10724/12223

Roberts, R. K., English, B. C., & Sleigh, D. E. (2000). *Precision farming services in Tennessee: Results of a 1999 survey of precision farming service providers* (No. 6). Department of Agricultural Economics and Rural Sociology, Tennessee Agricultural Experiment Station, University of Tennessee. https://www.researchgate.net/publication/237567376_Precision_Farming_Services_in_Tennessee_Results_of_a_1999_Survey_of_Precision_Farming_Service_Providers

Russo, J., (2014, September 29). *Precision Agriculture, Then and Now*. PRECISIONAg. https://www.precisionag.com/market-watch/precision-agriculture-then-and-now/

Schimmelpfennig, D. (2016). *Farm profits and adoption of precision agriculture* (No. 1477-2016-121190). https://doi.org/10.22004/ag.econ.249773

Schimmelpfennig, D. (2018). Crop production costs, profits, and ecosystem stewardship with precision agriculture. *Journal of Agricultural and Applied Economics*, *50*(1), 81-103. https://doi.org/10.1017/aae.2017.23

Schimmelpfennig, D., & Ebel, R. (2011). On the doorstep of the information age: Recent adoption of precision agriculture. *Economic Research Service, Paper No. EIB-80*. https://ssrn.com/abstract=2692052

Schimmelpfennig, D., & Ebel, R. (2016). Sequential Adoption and Cost Savings from Precision Agriculture. *Journal of Agricultural and Resource Economics*, *41*(1), 97–115. https://www.jstor.org/stable/44131378

Schimmelpfennig, D., & Lowenberg-DeBoer, J. (2020). Farm types and precision agriculture adoption: crops, regions, soil variability, and farm size. *Global Institute for Agri-Tech Economics Working Paper*, 01-20. http://dx.doi.org/10.2139/ssrn.3689311

Shockley, J. M., Dillon, C. R., & Stombaugh, T. S. (2011). A whole farm analysis of the influence of auto-steer navigation on net returns, risk, and production practices. *Journal of Agricultural and Applied Economics*, *43*(1), 57-75. https://doi.org/10.1017/S1074070800004053

Shockley, J., Dillon, C. R., Stombaugh, T., & Shearer, S. (2012). Whole farm analysis of automatic section control for agricultural machinery. *Precision Agriculture*, *13*(4), 411-420. https://doi.org/10.1007/s11119-011-9256-z

Smith, C. M., Dhuyvetter, K. C., Kastens, T. L., Kastens, D. L., & Smith, L. M. (2013). Economics of precision agricultural technologies across the Great Plains. *Journal of ASFMRA*, 185-206. https://www.jstor.org/stable/jasfmra.2013.185

Soha, M. E. D. (2014). The partial budget analysis for sorghum farm in Sinai Peninsula, Egypt. *Annals of Agricultural Sciences*, *59*(1), 77-81. https://doi.org/10.1016/j.aoas.2014.06.011

Sonka, S., & Cheng, Y. T. (2015). Precision Agriculture: Not the Same as Big Data But... *farmdoc daily*, *5*(70-2016-146). https://farmdocdaily.illinois.edu/2015/11/precision-agriculture-not-the-same-as-big-data.html

Srinivasan, A. (Ed.). (2006). *Handbook of Precision Agriculture: Principles and Applications.* https://doi.org/10.1201/9781482277968

Srinivasan, R., Shashikumar, B. N., & Singh, S. K. (2022). Mapping of Soil Nutrient Variability and Delineating Site-Specific Management Zones Using Fuzzy Clustering Analysis in Eastern Coastal Region, India. *Journal of the Indian Society of Remote Sensing*, 1-15. https://doi.org/10.1007/s12524-021-01473-9

Tey, Y. S., & Brindal, M. (2012). Factors influencing the adoption of precision agricultural technologies: a review for policy implications. *Precision agriculture*, *13*(6), 713-730. https://doi.org/10.1007/s11119-012-9273-6

Thompson, N. M., Bir, C., Widmar, D. A., & Mintert, J. R. (2019). Farmer perceptions of precision agriculture technology benefits. *Journal of Agricultural and Applied Economics*, *51*(1), 142-163. https://doi.org/10.1017/aae.2018.27

Torrez, C., Miller, N., Ramsey, S., & Griffin, T. (2016). Factors Influencing the Adoption of Precision Agriculture Technologies by Kansas Farmers. *Kansas State University Department of Agricultural Economics Extension Publication December*. https://www.agmanager.info/sites/default/files/pdf/Precision%20Ag%20Technology%20Adoption.pdf

U.S. Department of Agriculture (2018). *2018 Agricultural Resource Management Survey (ARMS): Phase 2- Field Crop Chemical Usage and Production Practices.* https://www.ers.usda.gov/webdocs/DataFiles/52816/W_2018_All_Phase2_Interviewers_Manual_M_COP_CPP.pdf?v=8015

Van Evert, F. K., Gaitán-Cremaschi, D., Fountas, S., & Kempenaar, C. (2017). Can precision agriculture increase the profitability and sustainability of the production of potatoes and olives? *Sustainability*, *9*(10), 1863. https://doi.org/10.3390/su9101863

Wang, H., & Wood, E. (2021). The Application of Precision Agriculture Technologies in US Pecan Production: Challenges and Opportunities. *Western Economics Forum*, 19(2), 20-27. https://doi.org/10.22004/ag.econ.315933

Whelan, B. M., & McBratney, A. B. (2000). The "null hypothesis" of precision agriculture management. *Precision Agriculture*, *2*(3), 265-279. https://doi.org/10.1023/A:1011838806489

Zhou, X., English, B. C., Larson, J. A., Lambert, D. M., Roberts, R. K., Boyer, C. N., ... & Martin, S. W. (2017). Precision farming adoption trends in the southern US. *Journal of Cotton Science*, *21*(2), 143-155. https://www.cotton.org/journal/2017-21/2/upload/JCS21-143.pdf