FARM OPERATOR PREFERENCES REGARDING SITE SPECIFIC WEED CONTROL ADOPTION

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

By

Devon John Schwarzrock

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

Major Department:
Agribusiness and Applied Economics

March 2024

Fargo, North Dakota

North Dakota State University
Graduate School

Title

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

MASTER OF SCIENCE

SUPERVISORY COMMITTEE:

Dr. Erik Hanson
Chair

Dr. Cheryl Wachenheim

Dr. Joao Paulo Flores

Approved:

04/09/2024 — Dr. Cheryl Wachenheim

Date — Department Chair

ABSTRACT

An increasingly popular use for unmanned aerial systems (UAS) is drone applied site-specific weed control (SSWC). Site-specific herbicide application allows applicators to target previously mapped weed clusters and spot sprays the targeted weeds individually. This benefits farmers by generating cost savings from reducing herbicide usage and limits overapplication of herbicide. This study aims to identify characteristics of spray drones that are desirable amongst farmers. A discrete choice experiment is used to identify attributes which farmers deem more valuable than others. This study finds that price, herbicide reduction rate, and application rate significantly impact a farmer's decision to rent or purchase a spray drone for SSWC use.

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ACKNOWLEDGMENTS

I would first like to thank God for giving me this opportunity to pursue this degree and for blessing me with the academic ability to succeed. Without Him, nothing is possible.

I give my most sincere thanks to my parents, Scott and Mandy Schwarzrock, for providing me with everything I needed in life, even when times were tough. Without the compassion or work ethic you instilled in me, I would not be where I am today. Your guidance has led me down this road, and I would not change a thing.

I would like to thank my academic advisors and professors that guided me throughout this education. Their teaching and willingness to assist in any matter, even if it wasn’t in their class or in their area of expertise, provided much needed reassurance through stressful semesters. I would like to especially thank my graduate advisor, Dr. Erik Hanson, for assisting me with my research and guiding me on the path towards graduation. Thank you to my graduate committee members, Dr. Cheryl J. Wachenheim and Dr. Joao Paulo Flores, for taking the time to assist me in my research and provide valuable feedback to ensure project integrity.

Lastly, I would like to thank all my friends and new family I met along the way at North Dakota State University for keeping me sane and giving me some of the best years of my life.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

ARMS ....Agriculture and Resource Management Survey

DCE..Discrete Choice Experiment

GIS ....Geographical Information Systems

GNSS ....Global Navigation Satellite Systems

GPS ....Global Positioning System

IIA ....Irrelevant and Identically Distributed

IID ....Independently and Identically Distributed

IRB ....Institutional Review Board

MLM ....Mixed Logit Model

NDVI...Normalized Difference Vegetation Index

OBIA...Object Based Image Analysis

PA ....Precision Agriculture

PAT ....Precision Agriculture Technology

SSWC..Site-Specific Weed Control

UAS...Unmanned Aeiral System

UAV ....Unmanned Aerial Vehicle

U.S. ....United States

USDA..United States Department of Agriculture

VRT...Variable Rate Technology

LIST OF APPENDIX TABLES

LIST OF APPENDIX FIGURES

1. INTRODUCTION

In the past few decades, the global agricultural industry has experienced significant changes. Global commodity markets, regional herbicide and pesticide markets, fertilizer markets, and energy markets have become increasingly volatile in recent years. To combat the side-effects of an increasing population and significant increases in volatility and risk in an ever-changing industry, the agricultural industry has witnessed a significant increase in technological advancements, especially in the equipment and precision agriculture technology fields. Precision agriculture can be described as the application of technology to manage temporal and spatial variability of crop production, with the goal of improving yields and environmental quality (Pierce and Nowak, 1999). Precision agriculture technologies (PATs) are equipment, software, hardware, and other tools that are used to minimize agricultural inputs while maintaining or improving agricultural output levels.

An attractive attribute of precision agriculture technologies is their potential to improve overall farm profitability while simultaneously reducing negative environmental impacts. A main goal in crop production is minimizing input costs while maintaining or improving yield levels, improving soil health, water quality, and air quality (Lowenberg-DeBoer and Erickson, 2019). With PATs, farmers can improve profitability by allocating adequate amounts of resources to necessary areas. This mitigates input overuse and allows for extra allocation of resources to nutrient deprived areas. PATs can also improve soil health by reducing overapplication of nutrients and chemicals into the soil profile. For example, applications of high volumes of herbicide have been shown to reduce concentrations of beneficial fungi, bacteria, and protozoa in soils (Kalia and Gupta, 2004).

Yield monitoring systems are largely regarded as the first widely adopted precision agriculture technology. Since the implementation of the yield monitor in the 1990s, adoption rates of precision agriculture technology have steadily increased. As more applications of precision farming and site-specific management practices entered into the market, the general popularity of precision agriculture as a whole has also increased (DeLay and Comstock, 2021). A study found that three main categories affecting the attitude to adopt precision agricultural technology are socio-demographic factors, competitive and contingent factors, and financial resources (Pierpaoli et al., 2013). According to the same study, level of producer education, farm size, annual farm income, and social pressures all play a key role in willingness to adopt new technologies. As precision agriculture continued to evolve and new technologies became available, the number of users adopting these technologies increased, but at a seemingly decreasing rate. The industry has seen an overall slowing of the adoption rate of additional technology that could be partially attributed to perceptions of precision agriculture benefits, variable farm incomes due to volatile market prices, and applicability of these technologies to individual farming operations (Erickson et al., 2017; Miller et al., 2019).

Farmer usage of unmanned aerial systems (UAS), commonly known as drones, for agricultural purposes has slowly increased in recent years. These UASs are often equipped with various sensors and high-resolution cameras to be used for weed mapping, identifying stand counts, providing yield estimates, and monitoring crop health. This allows quick and efficient collection of field data used to support the identification of potential problem areas in crop fields (Radoglou-Grammatikis et al., 2020; Tsouros et al., 2019) Although UASs can provide great benefits to farmers, their overall use is relatively low compared to other precision tools due to their high costs (DeLay and Comstock, 2021). Drone prices have begun to decline over the past decade, but costs of associated hardware (sensors and cameras) and software are still relatively high (Simelli and Tsagaris, 2015).

Although the use of UASs for herbicide applications is relatively new compared to other PATs, site-specific weed control practices have the potential to save farmers thousands of dollars per year on herbicide and fuel costs. Site-specific herbicide application allows applicators to target previously mapped individual weed types and clusters and spot spray the targeted weeds individually, resulting in reduced herbicide and fuel usage. Multiple studies have been conducted to identify the amount of herbicide reduced by using site-specific weed control practices, and findings range from 12% to 96% (Castaldi et al., 2017; Gašparović et al., 2020; Gonzalez-de-Soto et al., 2016; López-Granados et al., 2016; Szalma and Dürgő, 2021; Zanin et al., 2022). Most notably, most studies observed full weed control and no changes in crop yields. Adopting site-specific weed control practices has the potential to reduce herbicide usage, resulting in increased farmer profits and reducing negative impact to both soil health and environment.

1.1. Problem Statement

Since the turn of the 21st century, variable rate technologies (VRTs) have become increasingly popular for use in nutrient application, seeding, planting, lime application, and variable hybrid placement (Erickson and Lowenberg-DeBoer, 2022). Variable rate herbicide application, however, has not followed the same trend as other VRT methods. Figure 1.1, taken from the 2022 Precision Agriculture Dealership Survey (Erickson and Lowenberg-DeBoer, 2022), shows farmer use of variable rate technologies as estimated by retailers. As previously mentioned, studies find that that using variable rate herbicide practices can drastically reduce herbicide usage, resulting in potential thousands of dollars in savings annually for farmers (López-Granados et al., 2016; Szalma and Dürgő, 2021; Zanin et al., 2022). Based on these studies, one would expect adoption rates of VRT herbicide application technology to continue to increase, not decrease.

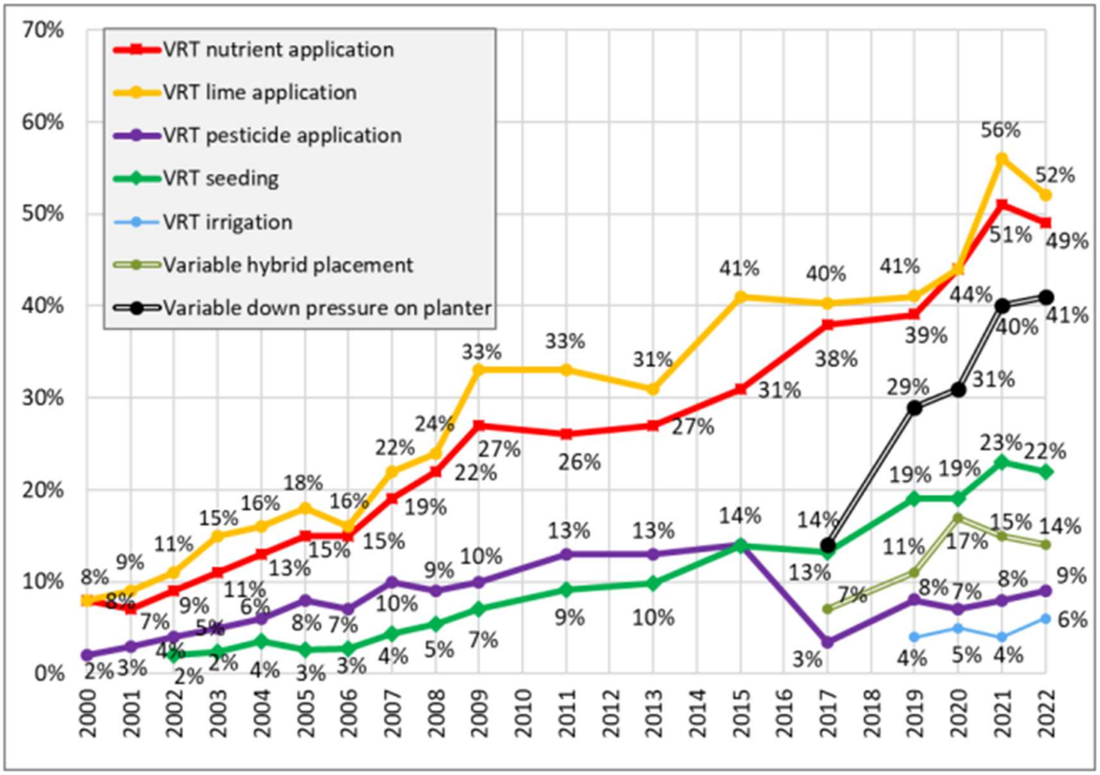

Figure 1.1 – Farmer Use of Variable Rate Technologies, Market Area Estimated by Retailers. Graphic taken from Erickson and Lowenberg-DeBoer (2022).

The two most common methods of applying herbicide via UAS are broadcast application and site-specific application. Broadcast application entails applying the herbicide across an entire area, such as a field. Site-specific herbicide application allows applicators to target individual weed types and clusters.

The implementation of site-specific herbicide application requires a method of collecting information on weed distributions in a target area and an application system capable of spot-applying herbicide. Weed map data is typically collected via high resolution drone imagery and then converted into weed control prescription maps and uploaded to the drone spraying software, which then only sprayed predetermined areas in the field. Although SSWC using UASs has the capability of reducing total herbicide usage, it requires multiple steps to perform efficiently and has limitations to imagery accessibility. Drone imagery requires installation of a high-resolution camera capable of capturing weeds and an intelligent operating system to identify weeds and their locations. These drones and cameras are often expensive and require an operator to fly and map the weed locations.

1.2. Research Objectives

This study aims to identify factors that affect willingness to pay for UAS herbicide application technologies, specifically spray drones used for site-specific weed control. This is accomplished by analyzing primary data collected via a discrete choice experiment survey administered to farmers in the upper Midwestern United States. The drone considered in the survey uses site-specific herbicide application with mapping data collected via prior drone flyover. Analysis of choice experiment results aims to identify desirable characteristics of spray drones based on demographic information, experience with precision agriculture technologies, and types of crops farmed.

2. BACKGROUND AND PREVIOUS STUDIES

2.1. Introduction

Developing and adopting new agricultural technologies has played a vital role in the evolution of agricultural production systems. Although the mechanization of agricultural practices has historically been uneven across the globe, the transition from traditional farming practices, such as manual and livestock powered tillage, to mechanized production using power systems in various agricultural applications led to increased productivity across the industry (Binswanger, 1986). The introduction of fertilizers, herbicides, plant and animal breeding technologies coupled with this mechanization of the agriculture industry has further increased farm productivity to attempt to meet the ever increasing global food demand (Pathak et al., 2019).

As these technologies continue to evolve, new technologies create better yield management practices that allow for increased precision in the agricultural production process. Precision agriculture (PA) is "a management strategy that gathers, processes and analyzes 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" (International Society of Precision Agriculture, 2021). Although PA technologies have the potential to improve production efficiency, many factors affect adoption rates and farmers' willingness to adopt the technology.

2.2. Precision Agriculture Adoption

Precision agriculture technologies encompass a wide variety of technologies applied to all aspects of agricultural production. Technologies in the PA industry include data collection technologies such as soil sampling and yield mapping, data process and decision making technologies like mapping software and geographical information systems (GIS), and application technologies such as VRTs and automatic steering (Say et al., 2018).

Precision agriculture technology adoption rates vary amongst farmers. The adoption of novel technologies in agriculture often experiences a time lag, which can be attributed to various reasons. PATs often have high up-front costs for equipment purchase and installation charges, along with monetary and opportunity costs of training on how to operate and maintain the systems. Multiple studies have been conducted to identify factors that affect the adoption rates of PATs. Pierpaoli et al. (2013) find that three main categories affecting the attitude to adopt precision agricultural technology are socio-demographic factors, competitive and contingent factors, and financial resources. The authors determine that farm size, annual farm income, level of education, and social pressures all contribute to willingness to adopt technologies. Multiple studies also conclude that farm size plays a significant role in adopting technology, finding that large farms are more likely to adopt PATs than smaller farms (Lowenberg-DeBoer and Erickson, 2019; Pierpaoli et al., 2013; Say et al., 2018; Schimmelpfennig, 2016; Schimmelpfennig and Ebel, 2016; Thompson et al., 2019). Smaller farms often operate with smaller profit margins, making high-cost investments less feasible.

Schimmelpfennig and Ebel (2016) find that resale value affects willingness to purchase PATs. PATs use data, information, and equipment specifically designed for individual farm operations. This makes it difficult for farmers to resell their equipment later, and farmers may require a high expected return on their investment in PATs. Although there are many factors that affect attitudes toward adoption, Thompson et al. (2019) find that 88% of responding PAT users believe PA technologies are crucial to their farm success, 80% believe PA use makes them better managers, and 77% find it simplifies their job. The same survey also found when choosing between cost savings and yield improvement, opinions were nearly split, 51% to 49%, respectively.

Though consumer preferences differ amongst farmers, there have been some discernable trends in the adoption of PATs. A recent study examining the adoption of digital agriculture technologies by United States (U.S.) farmers finds that adoption rates of PATs have been increasing since 1996, with adoption rates generally being higher for corn and soybean acres compared to winter wheat, cotton, sorghum, and rice (J. McFadden et al., 2023). The same study also finds that as of 2019, over half of all U.S. farm and ranch acres employ GPS technologies for production, with automatic guidance systems observing the greatest increase in adoption, with over 50% of acreage utilizing it across various crops. According to the United States Department of Agriculture (USDA) Agriculture and Resource Management Survey (ARMS), overall PA adoption increased from 2005 to 2016, but the rate of adoption varied by time period, with faster growth observed in the earlier years (DeLay and Comstock, 2021). The same survey also observed a shift towards bundled PA technologies, consisting of three or more individual tools. On an acreage basis, these bundles grew about 60% faster than on a farm basis, which suggests larger farms are more likely to adopt comprehensive precision agriculture strategies.

Overall, adoption of PATs has been trending upwards (Erickson and Lowenberg-DeBoer, 2022; Lowenberg-DeBoer and Erickson, 2019; J. McFadden et al., 2023), however adoption rates vary depending on the technology. Global Navigation Satellite Systems (GNSS) guidance, sprayer boom control, planter row shutoffs, and similar automated technologies have been adopted at a high rate (DeLay and Comstock, 2021; Erickson and Lowenberg-DeBoer, 2022;

Lowenberg-DeBoer and Erickson, 2019) while VRT adoption has been relatively slow, with only about 20% of farms using variable rate technology (Lowenberg-DeBoer and Erickson, 2019).

2.3. Variable Rate Technology Adoption

Variable rate application technologies are designed to reduce input costs by allowing farmers to apply inputs at varying rates within a field. However, variable rate technology has been adopted slower than most other PATs (Lowenberg-DeBoer and Erickson, 2019). This raises questions about whether farmers realize cost savings. A study conducted to determine if VRT was profitable determined that it offers additional cost savings when combined with soil mapping PATs, but offers no significant cost savings when paired with yield mapping (Schimmelpfennig and Ebel, 2016). The results suggest that VRT on its own may not offer significant cost savings but demonstrates a synergistic effect that generates greater cost savings when paired with other PATs. This suggests that when farmers debate VRT adoption, lack of ownership of synergistic equipment may affect their decision.

Variable rate technology has been applied to many practices in the agricultural industry, including fertilizer, lime, and herbicide applications, seeding, irrigation, hybrid placement, and planter down pressure (Erickson and Lowenberg-DeBoer, 2022). However, in most of these applications VRTs are paired with at least one other PAT. For example, VRTs are often paired with soil maps for variable nutrient application or UAS imagery for herbicide application. A study conducted by Bullock et al. (2009) aimed to determine the value of VRT by quantifying its value to support in VRT decision-making. The study analyzes data from Illinois corn fields to estimate economically optimal nitrogen application rates for each field using VRT. The authors find that VRT would have been profitable in six of eight fields if the site-specific information was freely available, however private markets are unlikely to provide sufficient site-specific information for VRT due to potential free riding. The study argues that developing cost-effective methods for collecting and distributing site-specific information is important in maximizing the economic benefits of VRT and suggests that policy intervention and public funding could help overcome market limitations and allow for greater adoption of variable rate technology.

VRT adoption is heavily influenced by its relatively high initial equipment and software costs, and whether the farmers perceived benefits of yield improvements and cost savings to justify the price (Lowenberg-DeBoer and Erickson, 2019; J. McFadden et al., 2023). As noted in Schimmelpfennig and Ebel (2016), VRT relies significantly on site-specific data such as soil and yield maps. Farmers who have already invested in these PATs are more likely to consider adopting VRTs for their farm operation (J. McFadden et al., 2023). The same study, focusing on the adoption of digital agriculture, finds that adoption rates of PATs such as yield and soil maps have increased in corn, soybean, winter wheat, cotton, rice, and sorghum production from 1996 to 2019. Figure 2.1, taken from the same study, shows overall adoption trends of VRT from 1998 to 2019 has increased among the same crop types. (J. McFadden et al., 2023). The rise in soil and yield mapping appears to be correlated with the rise in VRT adoption, suggesting that farmers with access to mapping PATs may also be adopting VRT technology.

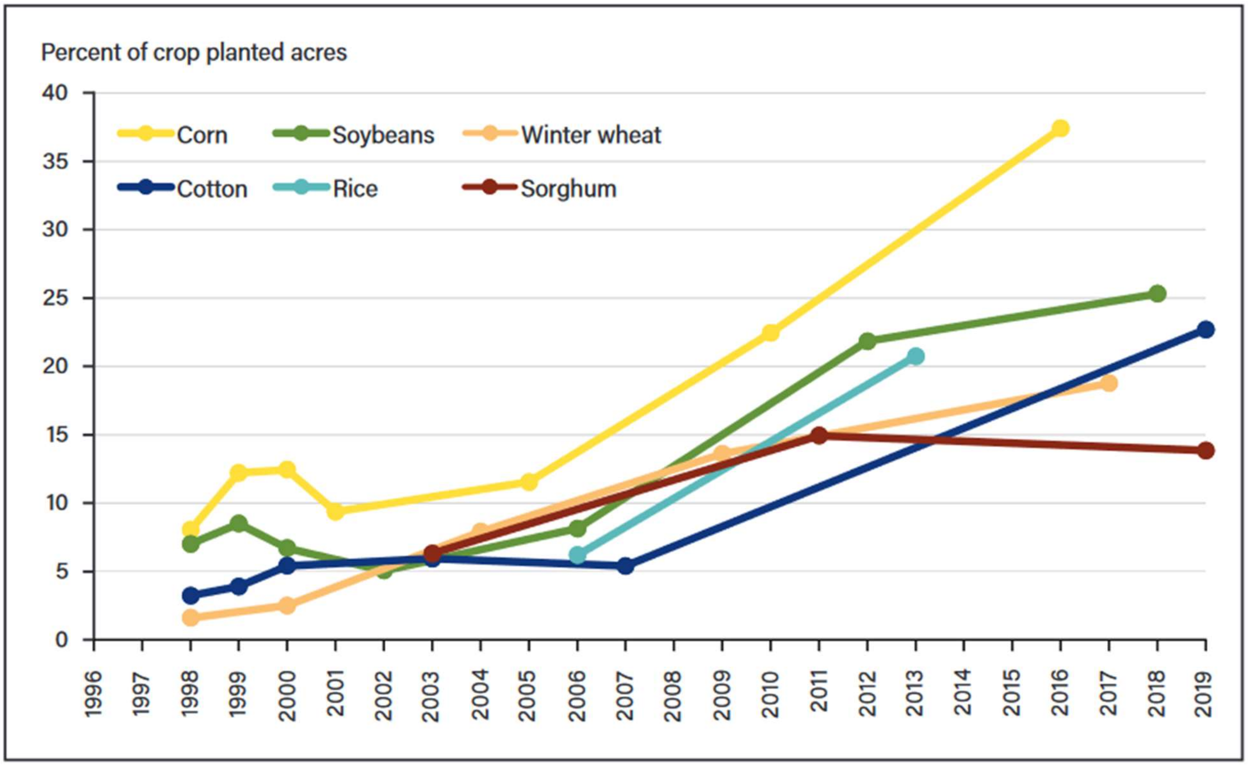

Figure 2.1 – Variable Rate Technology Use from 1996 - 2019.

Taken from McFadden et al., 2023.

2.4. Unmanned Aerial Systems (UASs) and Remote Sensing Applications

The use of UASs in precision agriculture has evolved since this technology's introduction into the industry. The most common use of UAS technology is remote sensing. This often involves equipping a UAS with a high-resolution camera or other sensors paired to an electronic smart device, flying over the target area to map the surface, and using these images to determine crop and landscape status.

Remote sensing systems have a variety of uses in precision agriculture. These include sensing crop yield and biomass, crop diseases, insect damage and infestation, weed mapping, crop nutrient and water stress, and soil properties like pH, organic matter, and moisture (Mulla, 2013). Satellite based remote sensing has been used since the 1970s. Satellite products have been used extensively for providing high spatial and temporal imagery used for monitoring crop status

(Sishodia et al., 2020). Although satellite image quality and capability have significantly improved since the 1970s (Mulla, 2013), satellite imagery is sometimes not the best option for crop monitoring purposes. Low spatial resolution of images acquired, limited availability of satellites to capture images, environmental factors such as cloud cover blocking sight lines, and long wait periods between acquisition and reception of images all hinder the effectiveness of satellite imagery (Tsouros et al., 2019). Using UASs for mapping and remote sensing allows for high-resolution images to be collected and used in PA purposes as needed.

In addition to remote sensing, UAS technologies have been applied to an assortment of PA tasks, including site-specific herbicide applications, stand count identification and disease detection. The most common applications of UASs for PA are: weed mapping and control; crop growth and health monitoring; crop yield estimation; disease detection; irrigation management (Tsouros et al., 2019).

As remote-sensing applications have evolved, they have been paired with new and emerging technologies. The introduction of machine learning into sensing technologies has created the ability to automatically detect and map existing and emerging weeds. These machine learning algorithms are programmed into the sensing technologies and allow for autonomous identification and logging of weed location in the target area. Research has found that using an object-based, machine learning method of weed identification achieved the highest accuracy, detecting 89.0% and 87.1% of weeds in oat fields (Gašparović et al., 2020). This study demonstrates the feasibility of using low-cost RGB cameras for effective weed detection, creating an opportunity for increased accessibility for farmers.

Hunter et al. (2020) paired two separate UASs, one using high-resolution UAS imagery with an object-based image analysis (OBIA) program to identify and map areas infested with target weeds, and one equipped with spraying capabilities to aerially apply herbicide to mapped weed patches. The study finds that integrating remote weed mapping and autonomous spraying UASs (UAS-IS) was 0.3 to 3 times more efficient than conventional broadcast herbicide application at identifying and treating only areas where weeds are present. The study also notes potential herbicide reduction by up to 60%, and that UAS-IS is more efficient in detecting and targeting patchy weed infestations compared to dense, uniform infestations (Hunter et al., 2020). Castaldi et al. (2017) find that UAS generated weed maps paired with variable-rate tractor applied herbicide achieved a 39% reduction in herbicide usage compared to conventional broadcast spraying.

Gonzalez-de-Soto et al. (2016) used an autonomous tractor equipped with on-board sensors for weed detection, direct-injection spraying boom designed to specifically target weeds, and a centralized controller to detect and eliminate weeds. This method was able to treat 99.5% of detected weeds and applied herbicide to approximately 0.5% of total area with no weeds. Zanin et al. (2022) used a self-propelled sprayer equipped with real-time sensors to detect plants and simultaneously apply herbicide, and reported a wide range of herbicide reduction, from 12% to 96%, with an average of 51% reduction. Szalma and Dürgő, (2021) paired normalized difference vegetation index (NDVI) imagery with a UAS equipped with spraying capabilities to spot apply herbicide and achieved up to 30% reduction in herbicide use. The various findings of these studies demonstrate there is some variability in the effectiveness of using site-specific weed control practices, but a common finding across all studies listed above is a reduction in the amount of chemical applied, some more significant than others. Nevertheless, SSWC creates an opportunity for farmers to potentially save thousands of dollars in herbicide costs yearly.

Although the precision SSWC practices have been shown to be effective in reducing herbicide usage, these technologies do have some drawbacks. Most studies using UAS imagery found that UAS operation is significantly reliant on weather conditions. High winds and other adverse weather conditions can alter drone flight paths in any drone use (Castaldi et al., 2017; Huang et al., 2018; Hunter et al., 2020; López-Granados et al., 2016). Various lighting and weather conditions can affect image analysis accuracy, creating a variance in weed detection. (Gašparović et al., 2020).

2.5. Impacts of Site-Specific Weed Control on Soil Health

It has been documented that herbicide use can be harmful to soil health and plant growth (Barman and Varshney, 2008; Kalia and Gupta, 2004; Latha and Gopal, 2010). In the soil ecosystem, microorganisms are essential for nutrient cycling, decomposition, and plant growth by breaking down organic matter, releasing available nutrients to plants, suppressing disease causing pathogens, and improving soil structure (Kibblewhite et al., 2008). Although herbicides are designed to target specific plant enzymes, they can inadvertently affect soil life by directly killing beneficial organisms or disrupting biological processes, such as nitrogen fixation and nutrient mineralization (Latha and Gopal, 2010; Rose et al., 2016). Disruption in soil biology can reduce crop health and productivity by altering soil structure, weakening disease resistance, and reducing nutrient availability (Rose et al., 2016).

Herbicides have been found to affect various soil microorganisms differently and the impact of herbicides on soil microorganisms is not uniform across herbicide chemistries. Herbicides have differing chemical properties and are applied at different rates, which affect the degree to which soil health is impacted (Barman and Varshney, 2008; Latha and Gopal, 2010). For example, butachlor, a pre-emergence herbicide, has been shown to significantly reduce populations of bacteria and actinomycetes for longer periods of time compared to 2,4-DEE and pretilachlor, herbicides applied postemergence (Latha and Gopal, 2010). The same study, however, found that overapplication of herbicides can cause a steady decline in soil microorganism population for at least 30 days, compared to soils with recommended dosage or soil where no herbicide was applied. This highlights the importance of not over applying herbicide. Some applied herbicides have mixed effects on soil processes. Glyphosate and 2,4-D, two very commonly applied herbicides, tend to kill populations of soil microorganisms, but have also been found to increase the rate of decomposition of organic matter in the soil profile, which releases nutrients essential to plant function (Barman and Varshney, 2008).

Overuse of herbicides has also been shown to cause herbicide resistance in target weed species. Target weeds exposed to repeated use of an herbicide or an herbicide with a similar chemical structure often adapt to resist these herbicides via target site mutations of protein structure, developing enzymes to break down the herbicide before it harms the plant, or developing the plant's cell walls or membranes to prevent herbicide absorption (Délye et al., 2013). High weed seed production stemming from large weed populations and short generation time for weed development can cause quick evolution of herbicide resistance in weed species, as multiple generations of the same weed family can occur in the same growing season (Délye et al., 2013).

Although herbicides can harm soils, the effects are usually not permanent as soils exhibit recovery potential. Latha and Gopal (2010) found that soils applied with herbicide at low rates trend to near normal microorganism counts around 30 days after application, with the lowest counts recorded 15 days after application. Soils the received overapplication of herbicides (rates higher than recommended ones) took much longer for microorganism populations to return to control levels. However, there are many other ways to mitigate effects of herbicide overapplication, such as adopting sustainable agricultural practices that enhance soil health. No-till farming, cover cropping, crop rotation, organic amendments such as composting and mulching, and integrated pest management are all sustainable agricultural practices that have been shown to increase or maintain soil health for plant growth and mitigate losses of both soil and nutrients (Barman and Varshney, 2008; Délye et al., 2013; Kibblewhite et al., 2008; Latha and Gopal, 2010)

3. METHODOLOGY

3.1. Data Collection

This study analyzes primary data collected via a discrete choice experiment survey distributed to farmers and farm decision makers in the upper midwestern United States. This survey was approved by the North Dakota State University Institutional Review Board (IRB) Protocol #IRB0004764, and distributed using Qualtrics XM, an online survey platform. The survey was distributed to farmers in Minnesota, North Dakota, and South Dakota via email, text message, and an online link from December 2023 to February 2024. The survey was conducted virtually, with subjects primarily accessing the survey via text message and email. Participation in this survey was strictly voluntary, and all responses were documented anonymously. All subjects were given access to a thorough description of the survey documenting their rights as a survey subject.

3.2. Survey Description

This survey presented farmers with two separate situations in which they were considering adopting a UAV spray drone for site-specific weed management purposes. The spray drone in this survey operates by spot-spraying weeds that had been previously identified by a PAT weed detection software via drone flyover or satellite imagery. The survey is separated into three portions, with the first collecting demographic information from the survey subjects. Subjects were explicitly informed of their ability to disclose as much or as little information as desired, as disclosing demographic information was not required for the survey. Demographic questions included gender, age range, education level, state farmed in, number of acres rented, number of acres owned, type of crops farmed, and existing precision ag technology used. This information is collected to analyze the differing preferences amongst different demographics. Demographic selections made available to the respondents are listed below in Table 3.1.

Table 3.1 - Demographic Survey Question Description and Levels Used in the Choice Experiment

Question	Description	Levels
Gender	Asks the gender of subject.	Male Female
Age	Asks the age range of survey subject. Ten-year intervals chosen for analysis.	Under 26 26 – 35 36 – 45 46 – 55 56 – 6566 and Older
Education	Asks what the highest level of education is received by survey subject.	Did not graduate high school High School Diploma / GED Attended Some College Associate's Degree Bachelor's Degree Some Graduate School Completed Graduate Degree or Higher
State	Asks what state the survey subject farms the majority of their acres in.	Minnesota North Dakota South Dakota Iowa
Acres	Asks for the approximate number of farmable acres the subject owns and rents. Two separate text entry boxes provided for "acres owned" and "acres rented."	Manual entry
Crops	Asks what crops are planted on the subjects' farm.	Corn Soybeans Wheat Other Small Grain Sugar Beets Edible Beans Potatoes Hay or Pasture Peas Other
PA Technology	Asks the subject if they currently use, or hire for use, precision agriculture technologies on their farm. Provides a short definition of precision agriculture technology to recipient: "Here, precision agriculture is defined as an approach to farm management that uses information technology to improve farm operation efficiency."	Do not use Precision Technology Global Positioning System (GPS) Yield Monitoring/Mapping Soil Sampling to Create Management Zones Auto-Steer and Guidance Satellite Imagery UAS or Drone Imagery Variable Rate Seeding Variable Rate Fertilizer/Lime Application Variable Rate Crop Protection Products Variable Rate Irrigation

3.2.1. Choice Experiment

The second and third portions of the survey are the discrete choice experiment (DCE). This DCE is used to identify which attributes of spray drones are valued by farmers. The DCE consists of two sets of ten questions, each presenting the subject with two hypothetical spray drones with differing quantities of the same characteristics in each set. XLSTAT, a data analysis and statistical software, was used to decide the combinations of attributes to present to the survey subjects. The first set of questions were assembled and compared based on a quarter factorial design recommended by XLSTAT. The second set of questions included one additional variable, and combinations of attributes were assembled and compared based on a reduced factorial design recommended by XLSTAT. Twenty profiles were generated for comparison across each set of ten questions in each section with XLSTAT eliminating scenarios in which a clearly superior option was created. In both sets, two of twenty options were eliminated based on theoretical superiority, resulting in eighteen profiles being compared across ten questions for each DCE section. Generated observations and combination data are included in Appendix A (Tables A1 through A4). In addition to the two options, a third opt-out option was included in each choice set. This allows the survey subject to decline both drone options they are presented, eliminating the assumption that the subject must pick between two options. This creates a more rational choice set, encompassing the individual's ability to decline the service all together and providing increasingly robust results (Kontoleon and Yabe, 2003).

The first set of ten questions presents the farmer with a hypothetical situation in which they are considering adopting the use of a spray drone for site-specific weed control practices by renting a drone from a local retailer. The survey then presents the farmer with two drones with differing characteristics, and they must choose between adopting "Drone A", "Drone B", or "neither." The descriptions of the varied characteristics of the spray drones are shown in Table 2. A sample survey question is shown in Figure 3.1.

Costs: $/acre | Capacity: gallons

Attributes	Choice A	Choice B
Rental Price	3	1.5
Herbicide Reduction %	65%	55%
Application Rate	30 acres/hour	16 acres/hour
Operating Cost	1.25	1
Spray Capacity	11	6

Figure 3.1 - Sample Survey Question, Survey Part 1

The second set of ten questions presents the farmer with a hypothetical situation like the first set. Here, the farmer is deciding whether to purchase a spray drone for future use. The survey then presents the farmer with two drones with differing characteristics, and they must again choose between adopting "Drone A", "Drone B", or "neither." The descriptions of the variable characteristics of the spray drones in the second set of questions are included in Table 3.2. A sample survey question is shown in Figure 3.2

Costs: $/acre | Capacity: gallons

Attributes	Choice A	Choice B
Purchase Price	18000	26000
Herbicide Reduction %	55%	65%
Application Rate	16 acres/hour	30 acres/hour
Operating Cost	1	1.25
Spray Capacity	6	11
Years Until Obsolete	2	4

Figure 3.2 - Sample Survey Question, Survey Part 2

Table 3.2 - Attribute Descriptions and Levels used in Discrete Choice Experiment

Choice set attributes	Description	Levels
Rental Price*	The cost per acre of renting the drone in $/acre.	$1.50 $3.00 $4.50
Purchase Price+	The cost of purchasing the drone in $.	$18,000 $26,000 $35,000
Herbicide Reduction	The percentage of herbicide reduction the drone application provides, compared to conventional spraying methods.	55% 65% 75%
Application Rate	The rate in acres per hour the drone can spray.	16 30 44
Operating Cost	The cost per acre of operating the drone. This includes costs such as recharging the drone, labor, etc. in $/acre	$1 $1.25 $1.50
Spray Capacity	The amount of herbicide (in gallons) that the spray drone can hold.	6 11 16
Years Until Obsolete+	Number of years until drone technology becomes outdated/obsolete. i.e., a better and more improved model is available.	2 4 6

[*] Attribute included in first DCE section only
[+] Attribute included in second DCE section only

Application rate, spray capacity, and purchase price attributes were collected from drones available on market. Operating cost and rental price are not representative of actual market prices. The software longevity value - years until obsolete - and herbicide reduction rate values were chosen based on estimates from previously conducted studies.

3.3. Model Description and Framework

A discrete choice experiment (DCE) is based on framework where the respondent is presented with multiple alternatives with differing levels of appropriate characteristics, and the subject chooses the alternative that gives them the highest expected utility (Čop and Njavro, 2022). Each alternative may have some attributes that are the same, similar, or vastly different variations, and based on these attributes, the respondent chooses the alternative that yields them the highest utility. DCE statistical analysis is based on McFadden's random utility model which theorizes individual i_x (where $i = 1, \ldots, n$) will always choose option j ($j = 1, \ldots, m$) in choice set C_t (where $t = 1, \ldots, T$) if j provides the highest level of utility of the options presented in the given choice set C (D. McFadden, 1973). Based on random utility theory, we assume utility of farmer n when choosing alternative i in choice set C_t ($t = 1, \ldots, T$) (U_{int}, unobserved) is made of a deterministic observable element V_{int} and a random ε_{int}:

$$U_{int} = V_{int}(X_{int}) + \varepsilon_{int}$$

where V_{int} depends on the attributes of alternative i faced by respondent n, X_{int} (Kuhfuss et al., 2016). Utility is ambiguous in the way that there is no natural level of it, nor is there a scale it can be measured in. Because of this ambiguity, there are many methods of estimation of utility in a discrete choice model. The goal of the model is to extract enough information on attributes amongst alternatives chosen or declined by respondents to identify characteristics that significantly affect perceived utility of respondents. Logit models, specifically conditional logit or nested logit are typically the foundation of many DCE analyses. In standard multinomial logit and choice-model conditional logit models, it is assumed that the error terms are independently and identically distributed (IID) across alternatives, and independence of irrelevant alternatives (IIA) assumption is required.

Although conditional logit models are proven effective in certain application, the IIA and IID assumptions in these models can encompass bias when implementing results from choice experiment analysis (Kuhfuss et al., 2016). The IIA assumption implies that irrelevant alternatives are independent across the population, implying homogeneity among respondent preferences. However, the choices of respondents are correlated across variables in the DCE. When sampling a population for choice experiment analysis, we know individuals exhibit unique preferences and likely do not share the same preferences. To analyze discrete choice analysis data effectively and capture the heterogeneity of subject preferences, one should relax these assumptions using a mixed logit or random parameter logit model.

Mixed logit models (MLM) are used in choice experiment analysis because they relax some of the restrictive assumptions observed in a traditional conditional logit model, such as the IIA assumption. By relaxing these assumptions, the model can record the diversity of farmer preferences and identify the preference specific to each respondent randomly distributed across the respondent population (Brownstone and Train, 1998). MLMs use random coefficients to model the alternative-specific variable correlation of choices across alternatives. In this application, the MLM models the probability of selecting each alternative for each question instead of modeling the probability for selecting each alternative. The term "mixed" in this context denotes that the model allows for both fixed effects and random effects. Fixed effects are factors that are assumed to be constant across all observations, while random effects allow for unobserved variability that may differ across entities.

Kuhfuss et al. (2016) use a binary-like model structure where if A_{int} is a dummy variable represented by number 1, if alternative i is chosen by farmer n in choice set C_t, then:

$$A_{int} = \{\frac{1 \text{ if } U_{int} > U_{jnt}, \forall j \ \in C_t, j \neq 1}{0 \text{ if } U_{int} \leq U_{jnt}, \forall j \ \in C_t, j \neq 1}$$

while assuming error terms ε_{int} are distributed IID among alternatives across the population and follow a Gumbel distribution. The conditional logit model representing the probability that respondent n chooses alternative i in choice set C_t is:

$$P(A_{int} = 1) = \frac{\exp\,(X'_{int}\beta_n)}{\sum_{j\in C_t} X'_{jnt}\beta_n}$$

where β is the vector of k preference parameters representing the weight of each characteristic included in the DCE on respondent preferences (Kuhfuss et al., 2016).

Using a MLM model to relax the IIA assumption, the preference parameter vector β_{kn} are specific to individual respondents and randomly distributed across the respondent population with a density function $f(\beta_k)$. The conditional probability that farmer n chooses alternative i in C_t is modeled as:

$$P(A_{int} = 1|\beta_n) = \frac{\exp\,(X'_{int}\beta_n)}{\sum_{j\in C_t} X'_{jnt}\beta_n}$$

And the probability of distinguishing the sequence of T choices by subject n is:

$$P(A_{in1} = 1, \dots, A_{inT} = 1) = \int \prod_{t=1}^{T} \left(\frac{\exp(X'_{int}\beta)}{\sum_{j\in C_t} X'_{jnt}\beta} \right) f(\beta) d\beta$$

where $f(\beta)$ is specified as normal or lognormal: $\beta \sim N(\mu,\sigma)$ or ln $\beta \sim N(\mu,\sigma)$, where μ and σ represent mean and covariance, respectively, of the distributions estimated by simulation (Kuhfuss et al., 2016; Train, 2009).

This study uses an MLM to analyze data collected from the discrete choice experiment, following methodology used by Kuhfuss et al. (2016) and proposed by Train (2009). The structure of the data collected from survey responses is better analyzed using panel-data structure and is analyzed via regression. This model was chosen because of its ability to analyze repeated observations on individuals choosing between alternatives while accounting for both observed and unobserved factors.

4. RESULTS AND DISCUSSION

4.1. Sample Characteristics

The survey received a total of 52 usable responses, determined by completion of the survey and choice experiment. Respondents were given the opportunity to end the survey at any time, resulting in multiple partial completions. Because the survey was separated into two parts (renting drone and purchasing drone), two separate analyses are conducted. Because the respondents reserved the right to end the survey at any time, 52 respondents completed the rental portion of the survey, with only 49 of 52 completing purchase set of questions. This results in 1,560 observations (52 respondents x 3 alternatives per question x 10 questions) and 1,470 observations (49 respondents x 3 alternatives per question x 10 questions) for the rental and purchase portions of the survey, respectively. Descriptive statistics are presented in Table 4.1

Table 4.1 – Discrete Choice Experiment Survey Respondent Population Characteristic

Question	Survey Respondent's Answers	Percentage of Survey Respondents
Age *What is your age (years)?*	Under 26 26-35 36-45 46-55 56-6566 and Older	15.4% 13.5% 13.5% 38.5% 11.5% 7.7%
Education *What is the highest level of education you have received?*	Did not graduate high school High school diploma/GED Attended some college Associate's degree Bachelor's degree Some graduate school Completed graduate degree	1.9% 11.5% 32.7% 21.2% 30.8% 0.0% 1.9%
State *In which state do you farm the majority of your acres?*	Minnesota North Dakota South Dakota Iowa	94.2% 1.9% 1.9% 1.9%
Crops Planted *What crops do you plant on your farm? Select all that apply*	Corn Soybeans Wheat Other small grain Sugar beets Edible Beans Potatoes Hay or Pasture Peas Other	100.0% 98.1% 30.8% 15.4% 0.0% 5.8% 0.0% 25.0% 0.0% 3.9%
Current PA use *Do you currently use, or hire for use, precision agriculture technologies on your farm?*	Do not use Precision Technology Global Positioning System (GPS) Yield Monitoring/Mapping Soil Sampling to Create Management Zones Auto-Steer and Guidance Satellite Imagery UAS or Drone Imagery Variable Rate Seeding Variable Rate fertilizer/lime application Variable Rate Crop Protection Products Variable Rate Irrigation	0.0% 88.5% 96.2% 71.2% 92.3% 51.9% 28.9% 30.8% 34.6% 7.7% 0.0%

The survey collected respondent ages by having them select the age range they were categorized in to. Results were collected from a variety of ages, with the highest percentage of respondents being 46 to 55 years old (38.5%) and the lowest being 66 and older (7.7%). The highest level of education received varied among the respondents, with most respondents having either attended some college (32.7%), completed a bachelor's degree (30.8%), or completed an associate degree (21.2%). Nearly all participants farmed most of their acres in Minnesota (94.2%).

Of all survey respondents, 100% report planting corn acreage on their farmland, and 98.1% report planting soybeans. Wheat (30.8%) and hay or pasture (25%) were the next highest reported crops planted by respondents. No survey respondents reported planting sugar beets, potatoes, or peas. These results are somewhat expected, as corn and soybeans were the most planted crops in Minnesota, with 7,9400,000 and 7,390,000 acres of corn and soybeans harvested, respectively, in 2022. Wheat and hay were the third and fourth most harvested crops in 2022 with 1,210,000 and 1,365,000 acres, respectively. (USDA National Agriculture Statistics Service, 2024).

Results varied when asked to identify PATs respondents currently use or hire for use. Nearly all respondents report using yield monitoring and mapping technologies (96.2%) or auto-steer/guidance systems (92.3%). Yield mapping and monitoring have become increasingly popular in recent decades, with many farmers using this data to track yield history and assist with hybrid selection for upcoming growing seasons to maximize outputs. These results are similar to the findings of the Precision Agriculture Dealership Survey, with guidance (autosteer) and yield monitoring being the most commonly used PATs (69% and 68%, respectively) with adoption rates trending upwards (Erickson and Lowenberg-DeBoer, 2022). Seventy-one percent of respondents indicate they use soil sampling to create management zones for their farmable acres. These management zones allow farmers to identify both soil quality and nutrient content, among other things, to determine necessary levels of nutrient application for their fields.

Of the survey respondents, only 28.9% report using UAS or drone imagery. This finding is slightly higher than the findings of the Precision Agriculture Dealership Survey, who report 17% of farmers used UAS imagery in 2022, but was trending upwards (Erickson and Lowenberg-DeBoer, 2022).

The survey also finds that 48.1% of the respondents use some kind of variable rate technology. This is notable because UASs used for SSWC combine UAS and VRT. This suggests that less than half of respondents may be familiar with VRT, which could affect responses. Of the VRTs surveyed, 34.6% of respondents report using variable rate fertilizer/lime application, while 30.8% report using variable rate seeding. These findings differ from the Precision Agriculture Dealership Survey, which reported 49% of farmers using VRT nutrient application, while only 22% reported using variable rate seeding (Erickson and Lowenberg-DeBoer, 2022). Schimmelpfennig (2016) reports that 28% of corn acres and 34% of soybean acres used VRTs according to the USDA Agricultural Resource Management Survey (ARMS) in 2010 and 2012, respectively. Although the results are dated, adoption rates were trending upwards toward values found by Erickson and Lowenberg-DeBoer (2022).

Overall, every respondent reports some form of PAT use, which implies some degree of familiarity with PATs, indicating the qualification of the respondents to take the survey. Total PAT use was reported higher than other studies, but that may be affected by the region surveyed. The Precision Agriculture Dealership Survey is administered across the entire United States, while this study targeted a small upper Midwestern region.

4.2. Empirical Results

To identify factors that affect adoption rates of UASs for SSWC in agriculture, two separate mixed logit models are used to analyze survey responses. Model 1 analyzes the first section of the DCE, where the respondents were asked about renting a spray drone. Model 2 analyzes the second section of the DCE, where the respondents were asked about purchasing a drone. Table 4.2 presents the results from both models.

Table 4.2 – Choice Experiment Mixed Logit Model Estimates

Variables	Model 1	Model 2
Rental Price	-0.371*** (0.074)	
Purchase Price		-0.170*** (0.023)
Herbicide Reduction	4.103*** (1.501)	3.489*** (1.268)
Application Rate	0.039*** (0.009)	0.061*** (0.013)
Operating Cost	0.168 (0.417)	-0.080 (0.567)
Spray Capacity	0.006 (0.014)	0.051** (0.026)
Obsolete Years		0.568*** (0.086)
Standard Deviation of Random Parameters		
Rental Price	0.118 (0.136)	
Herbicide Reduction	8.497 (1.523)	4.097 (0.980)
Application Rate	0.035 (0.011)	0.054 (0.018)
Operating Cost		0.172 (0.512)
Spray Capacity		0.082 (0.025)
Obsolete Years		0.235 (0.079)
Log Likelihood	-301.175	-275.093
Chi^2	51.33	85.05
Observations	1560	1458
Respondents	52	49

Standard errors reported in parentheses.

Significance levels: *** P < 0.01, ** P < 0.05, * P < 0.1

Operating cost and spray capacity in Model 1 and purchase price in Model 2 are classified as fixed variables, as their standard deviation when classified as random parameters were not statistically different from zero. All other variables in both models are classified as random with a normal distribution. Both models compare the utility associated with changes in each variable compared to the base alternative, which in this case is the "opt-out" option of selecting neither drone. Purchase price results are reported in thousands of dollars. Both models find price, herbicide reduction rate, and application rate to be statistically significant at the 1% level and find operating cost of the drone to be statistically insignificant. Although parameters were found to be statistically significant, interpretation of the raw coefficient values in a random utility model may not provide valuable information (Gramig and Widmar, 2018). However, the signs of these coefficients can be interpreted. A positive sign implies an increase in the value of the given attribute leads to an increase in utility. A negative sign implies an increase in the value of the attribute results in a decrease in utility.

Model 1 determines that as rental price increases, farmers perceive less utility. This is expected, as farmers are more likely to choose a cheaper alternative, when given comparable options. Purchase price reaches a similar conclusion in Model 2 where higher purchases prices are less preferred.

Herbicide reduction rate is found to have the most significant impact on perceived utility, as a greater reduction rate led to greater perceived utility. However, herbicide reduction rate is not a marketed characteristic when purchasing UASs for SSWC use, as it varies across cases and studies (Castaldi et al., 2017; Gašparović et al., 2020; Gonzalez-de-Soto et al., 2016; López-Granados et al., 2016; Szalma and Dürgő, 2021; Zanin et al., 2022). This implies that if developers can find a way to market expected herbicide reduction rates of using UASs for SSWC compared to conventional blanket spray application, farmers may value that attribute more and may consider adopting the UAS for use.

Operating cost is insignificant for both models. Recall that operating cost was defined as “the cost per acre of operating the drone…including costs such as recharging the drone, labor, etc.” This finding is unexpected because it implies that farmers may not consider operating cost to be significant in their decision of drone choice. However, this finding could be a result of prices being non-representative of market price or a lack of meaningful difference in attribute levels, as there was relatively little variation in the three operating cost values.

Spray capacity is insignificant to farmer choice when choosing to rent a drone for UAS use (Model 1) but is significant at the 5% level when purchasing a drone for use (Model 2). This finding is reasonable as it implies farmers do not significantly value the capacity of the UAS when choosing to rent a drone, and value other attributes such as rental price and application rate more. Farmers are more likely to have spray capacity affect their decision when purchasing a UAS for personal ownership because it directly affects how often farmers would need to refill their drone with herbicide, creating more work for the farmer.

Application rate, defined as acres sprayed per hour, is significant in both models, implying that greater application rates increase perceived utility. This finding is expected, as farmers have limited time to operate equipment and a faster rate of application leads to increased productivity.

The longevity variable, years until obsolete, was not included in Model 1, but was included in Model 2. This is because farmers are presented with a renting situation in Model 1, and the longevity of a drone they do not own should not affect their choice. Longevity is found to be significant at the 1% level in Model 2, determining an increase in expected longevity will increase perceived utility.

Sensitivity analysis is conducted using marginal analysis to identify the effects of a change in attribute levels on the likelihood of a farmer selecting a drone. Marginal analysis allows estimation of the effects of an alternative-specific covariate by changing values on one alternative's attributes. This identifies a change in the percentage of the likelihood an option will be selected compared to initial model results. Changing one variable affects the choice probabilities of selecting the other outcomes. In this case, rental prices decrease and increase by 10% and 20%. Table 4.3 shows the changes in probabilities of selecting each alternative after the change in price, compared to the original model. "A" "B" and "C" in each sensitivity analysis table represent Drone A, Drone B, and the opt-out option, respectively.

Table 4.3 – Sensitivity of Changes in Rental Price in Model 1

Drone A					
	Original Margins	20% increase	10% increase	10% decrease	20% decrease
A	0.341	0.317	0.329	0.354	0.368
B	0.535	0.558	0.547	0.522	0.510
C	0.123	0.125	0.122	0.122	0.121
Drone B					
	Original Margins	20% increase	10% increase	10% decrease	20% decrease
A	0.341	0.370	0.356	0.328	0.314
B	0.535	0.500	0.519	0.551	0.568
C	0.123	0.128	0.126	0.121	0.119

Results in Table 4.3 show that a 20% increase in rental price in Drone A results in 3.4% decrease (0.317) in the likelihood of selecting that drone, compared to the model determined probability (0.341) and a 20% decrease in rental price results in a 2.7% increase (0.368) in the probability the respondent will select Drone A. Similar results were found when changing rental price in Drone B. This indicates that the likelihood of an alternative being selected increases as rental price decreases, and vice versa.

The same sensitivity analysis using margins is also conducted on all other significant attributes in Model 1. Attributes are increased and decreased by 10% and 20% for Drone A in Table 4.4.

Table 4.4 – Sensitivity of Changes of Attributes of Drone A on Drone Selection Probability in Model 1

Herbicide Reduction					
	Original Margins	20% increase	10% increase	10% decrease	20% decrease
A	0.341	0.420	0.381	0.304	0.267
B	0.535	0.455	0.494	0.575	0.614
C	0.123	0.126	0.125	0.267	0.118
Application Rate					
	Original Margins	20% increase	10% increase	10% decrease	20% decrease
A	0.341	0.368	0.355	0.328	0.314
B	0.535	0.510	0.523	0.548	0.561
C	0.123	0.121	0.122	0.124	0.125

A 20% increase in herbicide reduction rate increases the probability of Drone A being selected by 7.9% and a 20% decrease lowers the probability by 7.4%. This marginal analysis shows that the likelihood of an alternative being selected increases as herbicide reduction and application rates increase and decrease as rates decrease.

Sensitivity analysis similar to Model 1 is conducted on Model 2 and its variables. Table 4.5 contains the sensitivity analysis on purchase price in Model 2.

Table 4.5 – Sensitivity of Changes in Purchase Price on Drone Selection Probability in Model 2

Drone A					
	Original Margins	20% increase	10% increase	10% decrease	20% decrease
A	0.492	0.405	0.447	0.538	0.586
B	0.321	0.381	0.351	0.289	0.256
C	0.187	0.215	0.201	0.173	0.158
Drone B					
	Original Margins	20% increase	10% increase	10% decrease	20% decrease
A	0.492	0.552	0.523	0.459	0.426
B	0.321	0.244	0.281	0.363	0.407
C	0.187	0.203	0.196	0.178	0.168

Like the price variable in Model 1, an increase in price leads to a decrease in the probability of a respondent choosing that alternative. However, in Model 2, the effect of a price change on probability is greater. A 20% increase in price for drone A decreases the probability of that drone being selected by 8.7% and a 20% decrease in price increases the probability of it being chosen by 9.4%. A 20% price increase of Drone A also increases the probability of the farmer choosing the opt-out option by 2.8%, which is a 14.97% increase from the original results. This indicates that the farmer would rather choose to not adopt than to pay a high price to purchase a UAS for SSWC.

Table 4.6 contains the same sensitivity analysis using margins on all other attributes in Model 2. Attributes increase and decrease by 10% and 20% for Drone A. Operating cost is omitted from sensitivity analysis due to model insignificance.

Table 4.6 – Sensitivity of Changes of Attributes of Drone A on Drone Selection Probability in Model 2

Herbicide Reduction					
	Original Margins	20% increase	10% increase	10% decrease	20% decrease
A	0.492	0.538	0.515	0.469	0.448
B	0.321	0.281	0.301	0.340	0.359
C	0.187	0.182	0.185	0.190	0.193
Application Rate					
	Original Margins	20% increase	10% increase	10% decrease	20% decrease
A	0.492	0.531	0.511	0.472	0.452
B	0.321	0.291	0.306	0.336	0.350
C	0.187	0.178	0.182	0.192	0.198
Spray Capacity					
	Original Margins	20% increase	10% increase	10% decrease	20% decrease
A	0.492	0.521	0.507	0.477	0.462
B	0.321	0.295	0.308	0.334	0.346
C	0.187	0.183	0.185	0.190	0.192
Obsolete Years					
	Original Margins	20% increase	10% increase	10% decrease	20% decrease
A	0.492	0.535	0.513	0.469	0.447
B	0.321	0.293	0.307	0.335	0.350
C	0.187	0.172	0.180	0.195	0.203

Herbicide reduction rate and longevity share a nearly identical effect on selection probability based on a sensitivity analysis (20% increase/decrease in herbicide reduction rate increases/decreases selection probability by 4.6%/4.4%). Sensitivity analysis shows that purchase price may have the greatest impact on likelihood of selection, as 20% changes in price have near double the effect on marginal selection choice probability. Longevity has the second greatest impact on opt-out rates, with a 20% decrease in longevity increasing the probability of the farmer opting out by 1.6% (8.6% increase from original value).

Marginal analysis is also conducted on demographic attributes of respondents. Each demographic level was given a coding number, and decisions are analyzed based on these levels. Table 4.7 lists the attributes of respondents and their respective levels.

Table 4.7 – Respondent Demographic Information Levels Used for Analysis.

Variable	Definition	Levels	Number
Age	Age range of respondents.	Under 26 26-35 36-45 46-55 56-65 66 and Older	1 2 3 4 5 6
Education	Highest level of education received	Did not graduate high school High school diploma/GED Attended some college Associate's degree Bachelor's degree Some graduate school Completed graduate degree	1 2 3 4 5 6 7
Crops	Number of crops farmed	2 – 6	2 – 6
PA Use	Number of PATs currently used	2 – 8	2 – 8

Because of the variability in the type of crops planted by respondents and relatively small sample size, there were few combinations of crops grown by many respondents with enough degrees of freedom to provide a significant result. Because of this, the "crops grown" demographic question was reclassified into the "number of crops grown" when analyzing trends. Similarly, "PA Use" experienced a large amount of variability in combinations of PATs used by respondents. The "PA Use" category was then reclassified to "number of PATs currently used" when analyzing respondent trends.

Marginal analysis finds that as age increased, the likelihood of selecting the opt-out option increases for both Model 1 and Model 2. Figure 4.1 and Figure 4.2 plot the marginal likelihood of each age range selecting Drone A, Drone B, or the opt-out option (A, B, and C respectively). Most notably, one can see in Figure 4.2 that as age increases, the likelihood of a farmer choosing to opt-out of purchasing a drone drastically increases, compared to the relatively slight increase in opt-out percentage for drone rental. This suggests that older farmers are less likely to purchase a UAS, compared to younger farmers. The finding that younger farmers are more likely to adopt a PAT is supported by other reports in the literature (DeLay and Comstock, 2021; Lowenberg-DeBoer and Erickson, 2019).

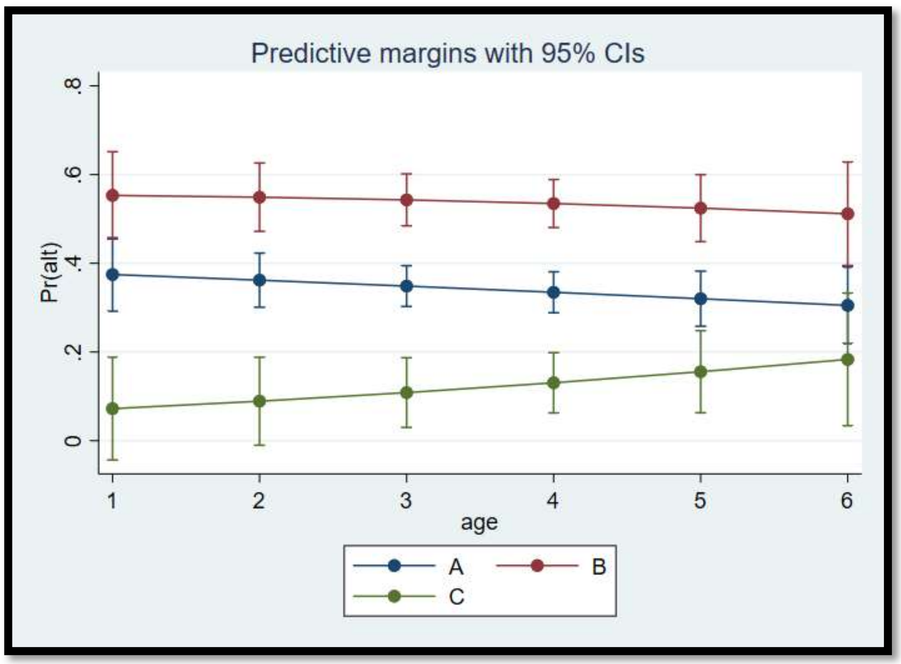

Figure 4.1 – Likelihood of Option Selection by Age Range, Model 1

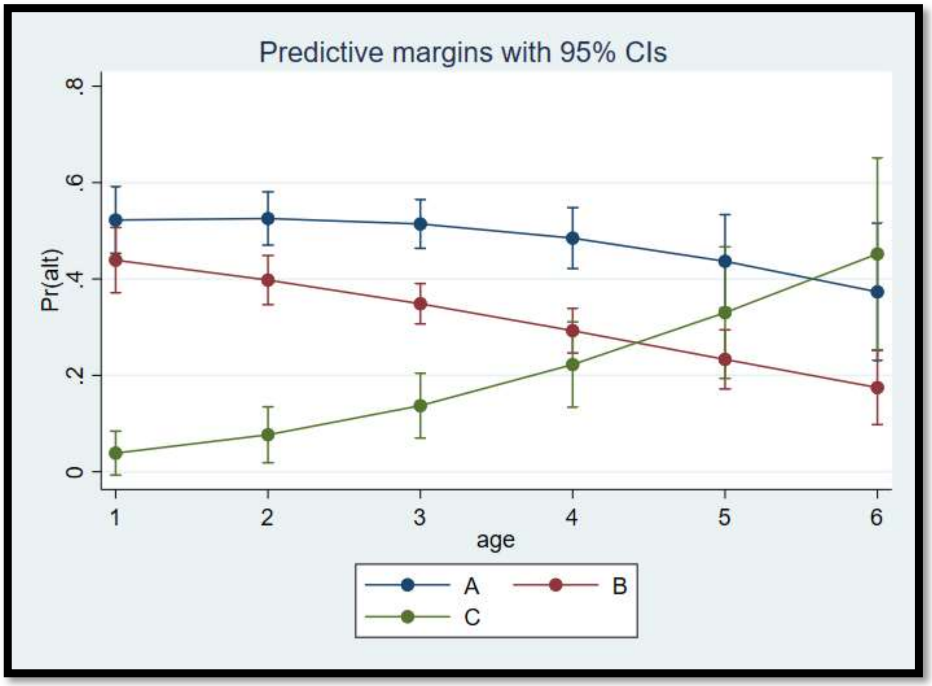

Figure 4.2 – Likelihood of Option Selection by Age Range, Model 2

Analysis also finds that as education level increases, the likelihood of a farmer choosing the opt-out option increases for both renting and purchasing a drone for use. This finding is rather unexpected, as other studies find that farmers with higher levels of education are more likely to adopt PATs (J. McFadden et al., 2023; Pierpaoli et al., 2013; Schimmelpfennig and Ebel, 2016). This finding could suggest that farmers with higher levels of education take other factors into account and are more hesitant to invest in relatively new and unproven technologies. This could be an area to conduct further research on.

Like education, this survey also finds that farmers who use a greater number of PATs are more likely to opt-out of purchasing or renting a drone. This finding is also unexpected, as other studies find that farmers with existing PAT use are more likely to adopt future PATs (DeLay and Comstock, 2021; J. McFadden et al., 2023; Pierpaoli et al., 2013). This could also imply that those with prior PAT use may be more informed in their decision, and would rather not adopt a technology at all, than adopt PATs with unappealing characteristic levels.

We also find that farmers who farm fewer numbers of crops are less likely to rent a UAS for SSWC use. However, the number of crops planted has a relatively little effect on likelihood of purchasing a UAS for use. The relatively low number of respondents results in even smaller numbers of respondents falling into demographic categories. This could create bias due to low degrees of freedom.

5. CONCLUSIONS

5.1. Conclusion and Implications

This survey presented farmers with two separate situations in which they were considering adopting a UAS spray drone for site-specific weed control purposes. The spray drone in this survey operates by spot-spraying weeds that had been previously identified by PAT weed detection software, via drone flyover. The weed maps are then converted into weed control prescription maps and uploaded to the drone spraying software, which then only sprayed predetermined areas in the field. The survey yielded significant results on preferred attributes and their weights when considering adopting a UAS for SSWC use.

5.1.1. Key Findings

This study finds that price, herbicide reduction rate, and application rate significantly impact a farmer's decision to rent or purchase a spray drone for SSWC use. Although herbicide reduction rate compared to broadcast application is not currently a marketable characteristic of a spray drone, its significance in this study shows the value in developing a marketable metric to identify average herbicide reduction. Spray capacity and software longevity also impact a farmer's decision to purchase a UAS for SSWC. Spray capacity is found to be insignificant when choosing to rent a drone for use. Operating costs are found to be insignificant for both renting and purchasing scenarios, however, this finding may have resulted from prices being non-representative of actual market prices and lack of meaningful difference in attribute levels.

Sensitivity analysis conducted using marginal analysis to test the effects of a change in attribute levels on the likelihood of a farmer selecting a drone finds that when choosing to rent a UAS for use, herbicide reduction rate has the greatest impact on drone choice, followed by rental price and application rate, respectively. When choosing to purchase a UAS for use, purchase price has the greatest impact on drone selection. An increase in the purchase price of one drone also increased the probability of the farmer declining both drones and selecting the opt-out option. This implies that a farmer would rather decline all both options and not adopt a UAS for use than overpay for one. Herbicide reduction rate and software longevity have nearly identical impacts on drone choice, followed by application rate and spray capacity, respectively. Software longevity has the second greatest impact on opt-out rates, where decreased longevity led to higher probability a farmer would decline both options.

Marginal analysis on demographics finds that as farmer age increases, the likelihood of the farmer selecting the opt-out option increases for both rental and purchase decisions. In other words, younger farmers are more likely to adopt a UAS for use than older farmers. As education level increases, the likelihood of a farmer choosing the opt-out option when renting and purchasing a drone increases. Farmers currently using a greater number of PATs experience the same trend. These findings are unexpected, as other studies find that higher levels of education and existing PAT use increase the likelihood of adopting other PATs (DeLay and Comstock, 2021; J. McFadden et al., 2023; Pierpaoli et al., 2013; Schimmelpfennig and Ebel, 2016).

5.1.2. Implications for Results

This study identifies areas that farmers value when considering adopting UAS SSWC technology. Manufacturers and sellers of this kind of technology can use this data to identify target markets and demographics to improve sales and increase PAT adoption rates. Significant attributes such as software longevity and demographic preferences on PAT adoption trends can apply to other PAT markets and can be used by researchers for marketing purposes.

5.2. Research Limitations

The biggest research limitation faced was obtaining survey responses from farmers. There was no incentive to influence farmers to complete the survey, creating a participation issue. Although the survey obtained 52 responses, a greater number of responses increases data accuracy and allows for greater analysis on demographic preferences of UAS attributes.

The attribute "herbicide reduction rate" is not a marketed attribute that farmers can choose from when adopting UAS technology for SSWC. Its inclusion allowed us to identify how being able to quantify the reduction in herbicide used by SSWC can influence farmers' decisions. If researchers could develop a metric to market reduced herbicide usage, adoption of SSWC would likely increase based on the results of the survey. However, other factors like weather and weed pressure and resistance affect the efficiency of SSWC, making it difficult to consistently quantify SSWC benefits.

Less than half of the survey respondents (48.1%) reported use of some variable rate technology. This combined with only 28.9% of respondents reporting existing use of UAS imagery technology could suggest unfamiliarity with UAS and site-specific weed control technologies. This unfamiliarity could lead to bias in survey results.

5.3. Suggestions for Further Research

To better identify the importance of specific variables to certain demographic ranges, more marginal analysis should be conducted similar to that conducted by DeLay and Comstock (2021). One could analyze the survey results based on demographic bundles, such as those who already use UAS and VRT technology, age and education level combinations, farmers who plant specific crops, etc. This type of analysis would allow for the identification of trends among certain demographics and could be used for marketing purposes. This would require a greater number of respondents to complete the survey to achieve a large enough sample size for analysis. Incentivizing survey responses may be an effective way to acquire more responses.

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APPENDIX A. SURVEY QUESTION DETAILS

Table A1 – Profiles in Rental Portion of Survey

Profile	Rental price (per acre)	Reduction in herbicide use	Application rate	Operating cost (per acre)	Spray capacity
1	1.50	0.55	16 acres/hr	1	12 liters
2	3	0.65	30 acres/hr	1.25	22 liters
3	4.5	0.75	44 acres/hr	1.5	32 liters
4	1.5	0.55	30 acres/hr	1.5	32 liters
5	3	0.65	44 acres/hr	1	12 liters
6	4.5	0.75	16 acres/hr	1.25	22 liters
7	1.5	0.65	44 acres/hr	1.5	22 liters
8	3	0.75	16 acres/hr	1	32 liters
9	4.5	0.55	30 acres/hr	1.25	12 liters
10	1.5	0.75	44 acres/hr	1.25	12 liters
11	3	0.55	16 acres/hr	1.5	22 liters
12	4.5	0.65	30 acres/hr	1	32 liters
13	1.5	0.75	30 acres/hr	1	22 liters
14	3	0.55	44 acres/hr	1.25	32 liters
15	4.5	0.65	16 acres/hr	1.5	12 liters
16	1.5	0.65	16 acres/hr	1.25	32 liters
17	3	0.75	30 acres/hr	1.5	12 liters
18	4.5	0.55	44 acres/hr	1	22 liters

Table A2 – Profiles in Purchase Portion of Survey

Profile	Purchase price	Reduction in herbicide use	Application rate	Operating cost (per acre)	Spray capacity	Years until obsolete
1	18,000	0.55	16 acres/hr	1	12 liters	2
2	26,000	0.65	30 acres/hr	1.25	22 liters	4
3	35,000	0.75	44 acres/hr	1.5	32 liters	6
4	18,000	0.55	30 acres/hr	1.5	32 liters	4
5	26,000	0.65	44 acres/hr	1	12 liters	6
6	35,000	0.75	16 acres/hr	1.25	22 liters	2
7	18,000	0.65	44 acres/hr	1.5	22 liters	2
8	26,000	0.75	16 acres/hr	1	32 liters	4
9	35,000	0.55	30 acres/hr	1.25	12 liters	6
10	18,000	0.75	44 acres/hr	1.25	12 liters	4
11	26,000	0.55	16 acres/hr	1.5	22 liters	6
12	35,000	0.65	30 acres/hr	1	32 liters	2
13	18,000	0.75	30 acres/hr	1	22 liters	6
14	26,000	0.55	44 acres/hr	1.25	32 liters	2
15	35,000	0.65	16 acres/hr	1.5	12 liters	4
16	18,000	0.65	16 acres/hr	1.25	32 liters	6
17	26,000	0.75	30 acres/hr	1.5	12 liters	2
18	35,000	0.55	44 acres/hr	1	22 liters	4

Table A3 – Profile Combinations per Question, Rental

Comparison	Profile 1	Profile 2
1	2	1
2	3	4
3	6	5
4	7	8
5	9	10
6	11	12
7	13	14
8	15	16
9	17	18
10	1	3

Table A4 – Profile Combinations per Question, Purchase

Comparison	Profile 1	Profile 2
1	1	2
2	4	3
3	5	6
4	8	7
5	10	9
6	12	11
7	14	13
8	16	15
9	18	17
10	3	1

APPENDIX B. SENSITIVITY ANALYSIS RESULTS

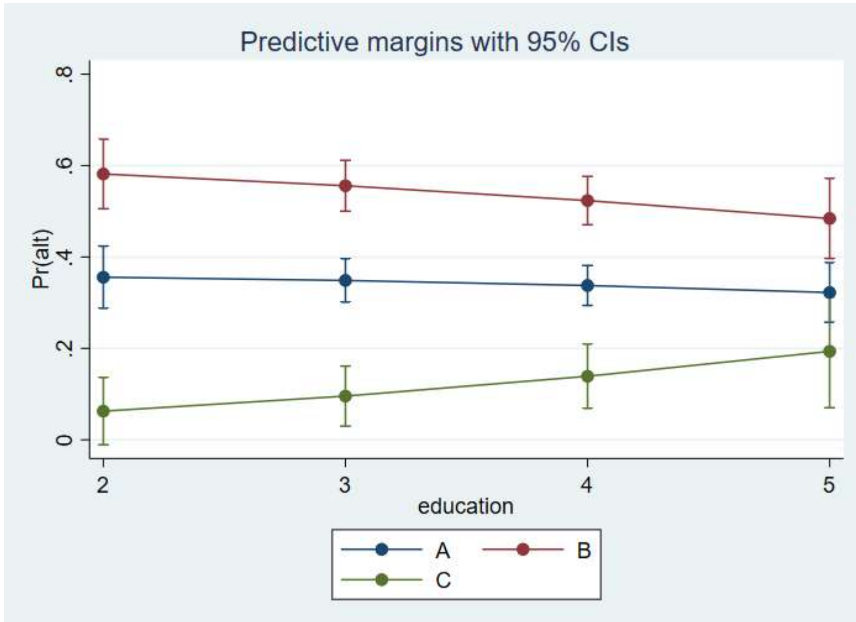

Figure A1 – Likelihood of Option Selection by Education Level, Model 1

Education levels 1, 6-8 were omitted from analysis due to low numbers of respondents.

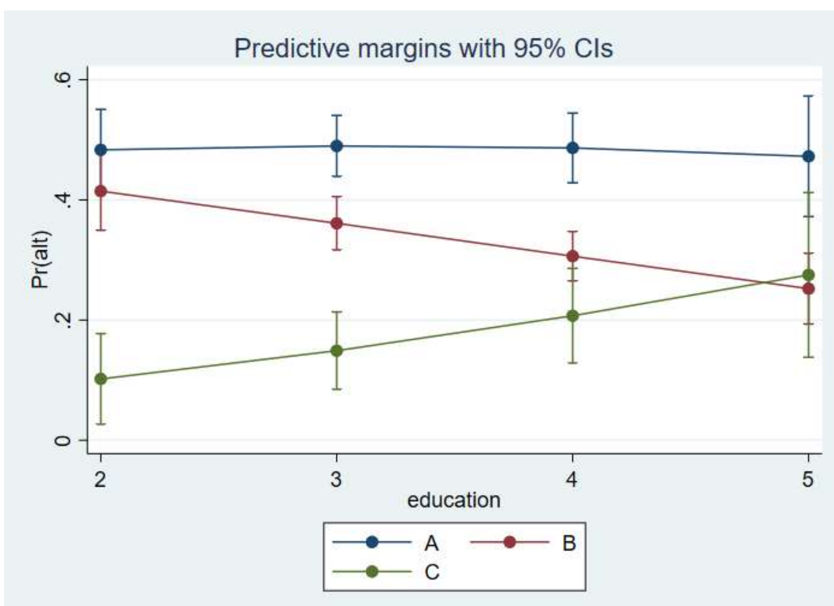

Figure A2 – Likelihood of Option Selection by Education Level, Model 2

Education levels 1, 6-8 were omitted from analysis due to low numbers of respondents.

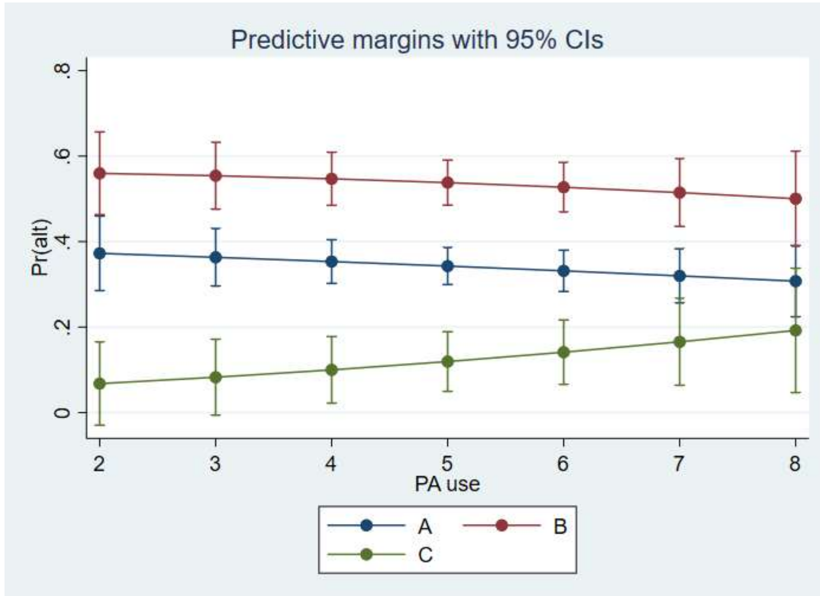

Figure A3 – Likelihood of Option Selection by Number of PAs Used, Model 1

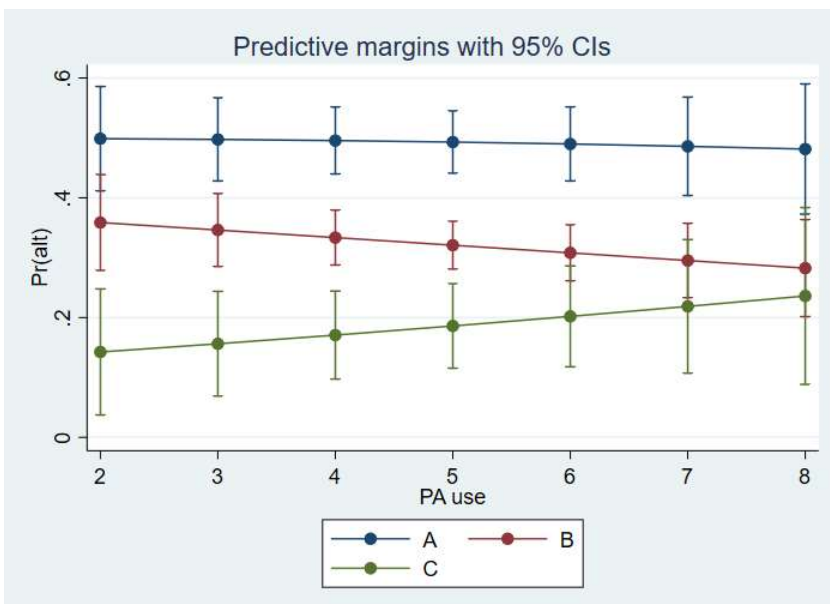

Figure A4 – Likelihood of Option Selection by Number of PAs Used, Model 2

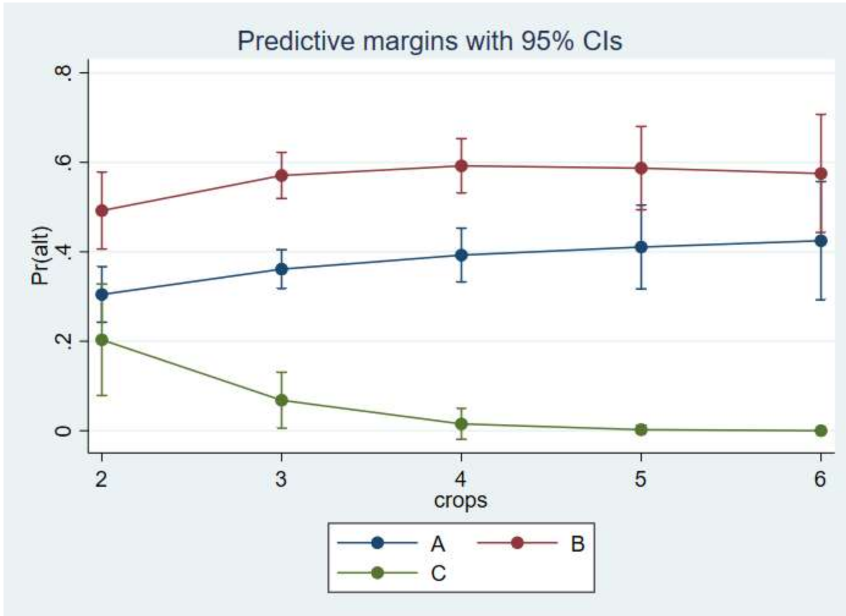

Figure A5 – Likelihood of Option Selection by Number of Crops Planted, Model 1

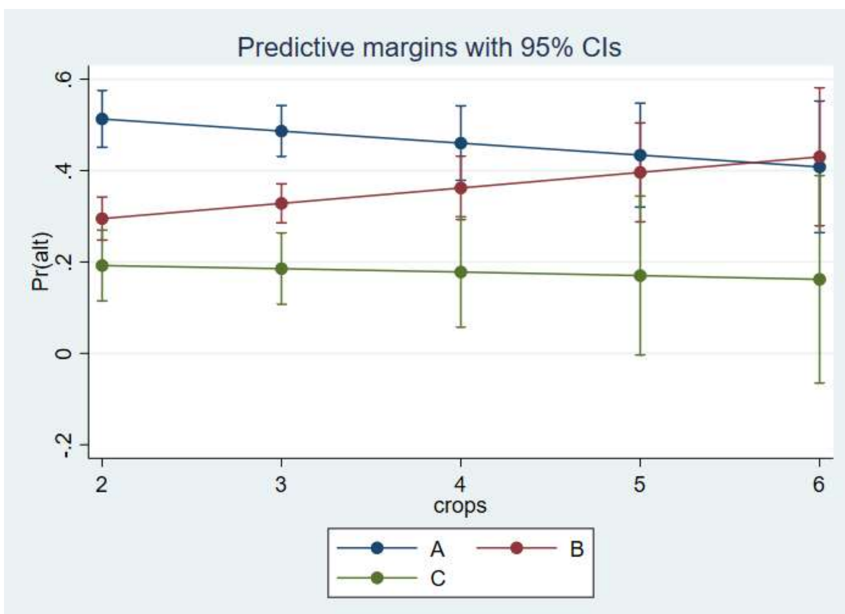

Figure A6 – Likelihood of Option Selection by Number of Crops Planted, Model 2