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Surveys

Understanding farmer views of precision agriculture profitability in the U. S. Midwest

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ABSTRACT

Precision Agriculture (PA) technologies are well known to be useful in addressing field heterogeneities and enabling informed site-specific management decisions. While profitability is the foremost factor considered by farmers when making PA adoption decisions, information in this regard is lacking from the farmers' perspective. This paper analyzed 1119 farmer responses from a 2021 survey conducted in four states along the western margins of the U.S. Midwest. Our findings show that while most (around 60%) non-adopters indicate that they are unaware of PA profit change, adopters are likely to rate a major profit increase. About two thirds of adopters rated at least a 5% increase in profitability towards variable rate (VR) fertilizer application (72%), VR seed application (68%), and automatic section control (66%). We modeled farmers' profit change subsequent to PA adoptions. Our regression results demonstrate that the profits from PA usage increase over time and that use of conservation practices likely influences PA profitability in a positive way. As soil quality and weather factors also affect profit ratings, it would be beneficial to compare and demonstrate profitability potential of various PA technologies on a regional basis and tailor the promotion efforts to farmers most likely to benefit from them.

1. Introduction

The introduction of PA technologies led to a paradigm shift in the farming sector as they address the heterogeneities of the field and enable informed site-specific management decisions (Aubert et al., 2012). By accounting for the spatial and temporal variability, PA has the potential to contribute to the agriculture sector in terms of improving farming efficiency, increasing crop production, enhancing economic viability, and reducing environmental problems (Finger et al., 2019; Khanna, 2021).

PA technologies can be divided into several categories. Georeferencing technologies, using global positioning system (GPS) or global navigation satellite system (GNSS), allow the use of guidance systems and controlled traffic. They are also referred to as embodied-knowledge technologies, or automated technologies, as no additional skills are required to use them. By locating positions of interest accurately and avoiding overlaps and skips, georeferencing technologies generate immediate benefits to farmers in saving input cost and reducing work time (Tey and Brindal, 2012).

In contrast to the embodied-knowledge technologies, information intensive technologies, or data technologies, require additional skills or training to be utilized effectively. Information intensive technologies comprise diagnosis technologies and application tools (Nowak, 2021). Diagnostic technologies, including sensors, satellite images, unmanned aerial vehicles (UAVs), and yield monitors, gather farm information using different technologies at various scales during the growing and harvesting period. Application tools, also referred to as variable rate technologies (VRT), enable site-specific management responses based on information gathered from diagnostic technologies. Through tailoring input usage to crop needs, VRTs also provide environmental benefits. For example, variable rate (VR) fertilizer application helps lower nitrate in groundwater and downstream water sources, thereby reducing agricultural non-point source pollution (Biermacher et al., 2009).

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Adoption rates vary across PA technologies. While technologies under the embodied-knowledge technologies are adopted rapidly, adoption rates of information intensive technologies remain relatively low (Lowenberg-DeBoer and Erickson, 2019; McFadden et al., 2022a). The low adoption rates could be due to a sequential adoption pattern (Griffin et al., 2017). While some farmers use diagnostic tools to collect data, not all use their collected data to facilitate management decisions (Thompson et al., 2021). Furthermore, PA tools require time to learn and complexities associated with information intensive technologies may pose a constraint for adoption (Miller et al., 2019).

Most importantly, farmers' PA adoption and investment decisions hinge on profitability (Batte and Arnholt, 2003; Adrian et al., 2005; Tey and Brindal, 2012). Uncertainty in profitability, compounded by high costs and feasibility concerns could dampen farmers' desire to adopt (Tey and Brindal, 2012). Therefore, knowledge about the economic implications of PA adoption is of paramount importance, especially under the circumstances of narrowing crop margins. To enhance PA adoption rate and ensure long-term farm sustainability, it is important for producers to gain a better understanding of PA induced profit changes.

Profitability is one of the most studied dimensions of PA for row crops, and PA usage can boost profit through reduced cost, increased productivity or both (McFadden et al., 2022a, 2022b; McFadden et al., 2023). However, there is a lack of consensus among existing literature on how PA affects farm profitability. On the positive side, most research indicated profit increases associated with PA usage in corn and soybean production (Griffin et al., 2004). Of the 210 reviewed early studies on PA profitability, 68% reported benefits from certain PA technologies (Griffin and Lowenberg-DeBoer, 2005). GPS mapping, guidance systems and VRTs were found to generate small to moderate positive effects towards profit in some studies (Schimmelpfennig, 2016, 2018). Yet PA technologies do not necessarily generate an increase in profitability (Biermacher et al., 2009). For example, Dhoubhadel (2021) found that when controlling for the known farm characteristics that influence the adoption decisions, there is no significant differences in net returns between adopters and non-adopters of PA.

Economic returns from PA adoption could vary across locations, fields, farmers, and crops (Khanna and Miao, 2022). While previous literature has evaluated the economic profitability associated with PA technology, most studies are case specific, which only focus on one or two specific technologies and one region. No study has examined factors that potentially affect the effect of PA adoption on profit change across farms and regions (Khanna, 2021). Furthermore, differing impacts of various PA technologies on profitability have received little attention. This paper intends to fill in these gaps. Our objectives are two-fold: 1) we will compare adopters' rated profit changes for a range of PA technologies; 2) we will study a variety of factors that potentially affect profit change to understand the source of variance in PA profitability.

The rest of the paper proceeds as follows. In the next section, we provide a literature review on how different PA technologies contribute to profit increase. In the three subsequent sections, we describe our survey procedure as well as selected regions and farms, explanations of the empirical models, and variables involved in the model estimation. Then we present our results and discussion section followed by the conclusions.

2. Profit increase potential for different precision agriculture technologies

Convenience is the most likely perceived benefit for georeferencing technologies (Thompson et al., 2019). The auto-steering and guidance systems help farmers navigate the field more efficiently and accurately on the desirable paths (Edge et al., 2018). Such systems can help boost profitability by increasing the accuracy in placement of the inputs through eliminating overlaps and skips, as well as reducing machinery costs due to enhancement in machinery field capacity (Shockley et al., 2011). Complementary to auto-steering and guidance system, automatic section control (ASC) improves input use efficiency and saves input cost by automatically turning off sections, nozzles, and rows on the agricultural sprayers and planters in areas that inputs have been previously applied or in areas designated as non-suitable for crop production (Shockley et al., 2012; Edge et al., 2018). The input cost savings from ASC adoption were evaluated and a higher profit increase potential associated with ASC was achieved in smaller and more irregularly shaped fields (Shockley et al., 2012; Velandia et al., 2013). Greatest increase in net returns were found when the ASC is used in combination with the guidance systems (Smith et al., 2013). Such profit increase is due to the more efficient use of inputs, thus farmers can see greater benefit if the input costs increase (Smith et al., 2013; Velandia et al., 2013).

VRTs facilitate input applications at heterogenous rates across different locations of the field. The input rates from nozzles or feeders can be adjusted by controllers using a computer program (Schimmelpfennig, 2016). Findings of Thompson et al. (2019) indicate that yield improvement and cost savings were the most perceived benefits for VR fertilizer application. Field characteristics, such as heterogeneity of soil conditions and spatial clustering of soil types, could affect the economic benefits of VRT (Späti et al., 2021). Input costs will also affect the economic benefits from PA technologies. As the seed and fertilizer costs continue to rise, the PA technologies that are associated with input cost savings, such as ASC and VRTs, will become more attractive to farmers (Velandia et al., 2013). In addition, the profitability increases associated with PA usage are not limited to input savings. For example, VRTs could also generate price premiums due to improved crop quality, such as increased protein content in wheat (Karatay and Meyer-Aurich, 2020).

Data collection and interpretation are the prerequisites for VRT implementation. Therefore, the resolution or accuracy of the data will affect the efficiency of VRTs. Remote sensing information is useful in detecting nutrient deficiencies, insect and weed issues, soil water deficiencies or excesses in various locations of the field (Tenkorang and Lowenberg-DeBoer, 2008). Recent improvements in remote sensing, such as satellite and unmanned aerial vehicle (UAV) remote sensing, are expected to increase VRT efficiency as well as the farm profitability (Späti et al., 2021).

Satellite imagery provides reliable high-resolution data obtained at relatively low or even no cost but may incur further costs in processing and creating prescription maps (Späti et al., 2021). Furthermore, its availability is contingent on weather conditions and only has periodic coverage (Zhang and Kovacs, 2012). The use of UAVs or drone-based remote sensing in PA sector has exponentially increased in the last decade (Maes and Steppe, 2019). Compared to satellite imagery, UAV remote sensing offers higher temporal and spatial resolution and is less affected by weather conditions (Zhang and Kovacs, 2012; Maes and Steppe, 2019). Other benefits of UAV remote sensing include fast set-up time, and low acquisition and maintenance costs (Maddikunta et al., 2021).

Different PA technologies adopted by farmers over time may complement each other and the cumulative benefit could be well beyond the cost savings and efficiency gains of an individual technology. Farmers can also reap additional profit due to increased value from differentiated production and enhanced farm value (Boehlje and Langemeier, 2021). Furthermore, the value of PA could potentially stem from reduced down time, better capacity utilization, and reduced risk of yield loss from weather events.

3. Survey description

We conducted a farmer survey during July–September 2021 to better understand the adoption status of PA technologies and conservation practices, as well as the benefits and challenges farmers may have encountered when using PA technologies. Our survey contains five sections and 34 questions, which requires about 15–20 min to complete.

The answers of respondents are kept confidential and are not linked with their names. The survey covered four states along the western margins of the U.S. Midwest, namely North Dakota, South Dakota, Minnesota, and Nebraska. Agricultural production is the major contributor to the region's economy.

In North Dakota and South Dakota, we selected counties east of the Missouri River to focus on the major corn planting regions. Seven counties in the northwestern North Dakota were excluded as they are more intensive in wheat production, but less intensive in corn-soybean rotation. We also excluded the northeast and southeast regions in Minnesota, which are primarily covered by forest and dairy silage/hay respectively. In Nebraska, we excluded the Northwest, North Central and Southwest regions, which contain the Sand Hills area with limited land suitable for crop cultivation purpose.

Large investment required by PA technologies in capital and learning time discourages PA adoption on small farms (Adrian et al., 2005; Pierpaoli et al., 2013; Lambert et al., 2015; Tamirat et al., 2017). Therefore, we use the screening criterion that each farm chosen grew at least 100 acres of corn. We purchased farmer mailing addresses from Dynata (dynata.com) and our mailing sample consists of contact information for 1500 randomly selected farmers in each state (so 6000 farmers in total). The farmer number selected in each county is proportional to the number of total eligible corn farmers in the county. The number of farms for each selected county is displayed in Fig. 1.

Based on the modified Tailored Design Method (Dillman et al., 2014), the 6000 operations were contacted up to four times. In the first wave, an advance letter was sent with a link to answer the questionnaire online. In the second wave, those who did not respond were then mailed the paper questionnaires with prepaid return envelopes. We sent a reminder postcard in the third wave, and then a second copy of the paper survey and pre-paid envelopes in the fourth wave. To enhance response rates, a \$2 bill was sent with the advance letter to all 6000 farmers regardless of their response status. Furthermore, survey respondents were also offered the chance to win one of the ten \$100 gift cards. Out of 6000 addresses, 101 were non-deliverable and 426 addressees indicated they were no longer farming. We received 1119 responses out of 5473 eligible addresses, indicating a response rate of 20.4%. Out of all survey respondents, 25.9%, 19.8%, 31.2% and 23.1% are from South Dakota, North Dakota, Minnesota, and Nebraska, respectively.

To capture the potential effects of weather and soil characteristics on PA profits, we merged the farmer survey responses with the county-level weather data from Parameter-elevation Regressions on Independent Slopes Model (PRISM) and soil information from gridded Soil Survey Geographic (gSSURGO) and the Soil Survey Geographic (SSURGO) databases supplied by NRCS. We purchased the latitude and longitude coordinates for the largest crop land unit (CLU) associated with each farm and created 1-km buffer for each CLU with average soil variable information calculated.

4. Empirical model

The empirical model was developed to understand factors that affect adopters' views towards PA profitability. Unlike some studies, we did not compare the net revenues of adopters against those of non-adopters and evaluate the effect of adoption on profitability. Instead, we asked how adopters rate their profit change after adopting the listed PA technologies with six categories provided ('Reduced by >10%', 'Reduced by 5-10%', 'Little change (within 5%)', 'Increased by 5-10%', 'Increased by >10%' and 'No idea'). In this way, adopters' answers directly reflect their views about the factual profit changes after adopting each of the listed PA technologies. Non-adopters were excluded from the modeling sample as their views of profit changes were perceived as counterfactual. We also excluded the 'no idea' category from the analysis due to its non-ordinal nature. It is worth noting that our dependent variables are essentially the treatment effects on the treated (ATT) in standard discrete choice models. Unlike some studies who used profits reported by non-adopters and adopters to represent profits before and after adoption, our dependent variables capture percentage of profit changes rated directly by adopters when comparing their own profits before and after adoption, thereby incurring no

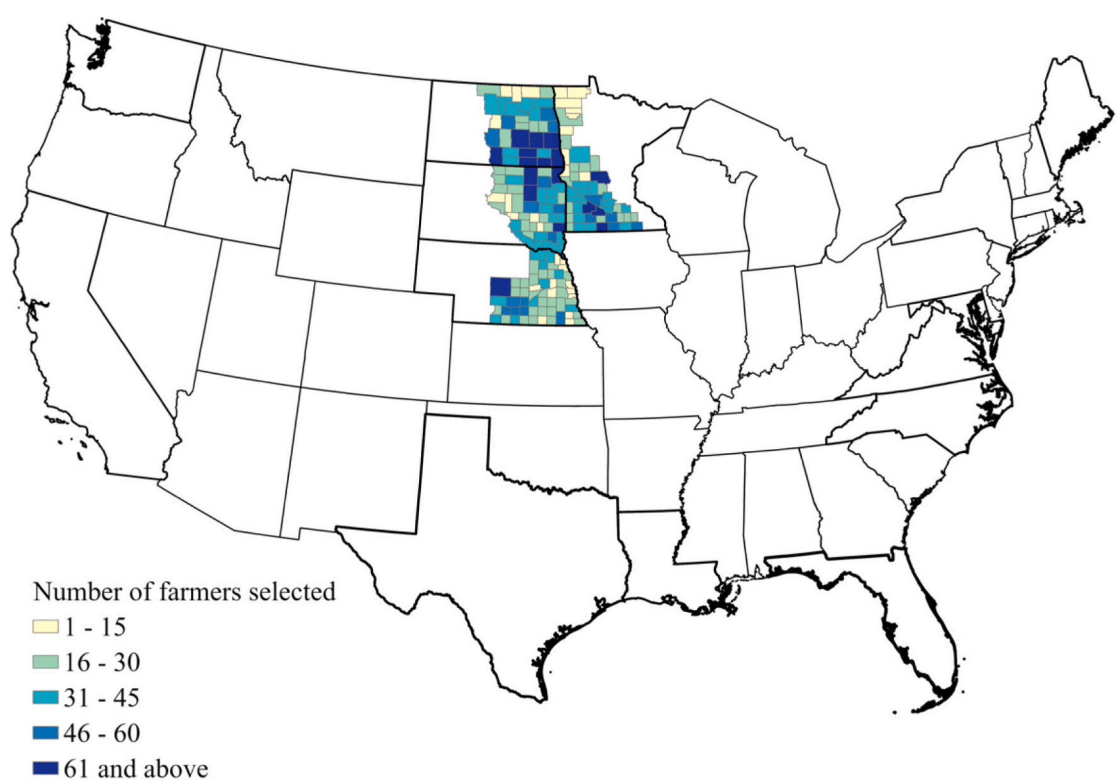

Fig. 1. Number of farmers surveyed in each selected county for 2021 Midwest farmer survey (Total sample size: 6000).

selection bias to be treated.

The dependent variables of our regression models are the adopter rated profit changes following adoption of different PA technologies in five ordinal categories ('Reduced by >10%', 'Reduced by 5-10%', 'Little change (within 5%)', 'Increased by 5-10%' and 'Increased by >10%'). These dependent variables follow the structure of censoring data as we only know the certain intervals they fall in but not their exact values. Censoring data modeling, also referred to as survival analysis, was first used in the medical research to process death or failure data. Later, it was expanded to analyze time intervals such as unemployment duration in labor economics (Ganjali and Baghfalaki, 2012). Recently it was also used to analyze willingness to pay (WTP) intervals and profit change intervals from survey data (e.g., Jeffcoat et al., 2012; Wang et al., 2020; Wang et al., 2021).

Interval censored data regression model, also referred to as interval regression model, can be treated as an extension of the Tobin model (Amemiya, 1973; Peto, 1973). The econometric specification of our interval regression model was:

$$Y_k^* = X_k\beta_k + U_k \ (k = 1, \cdots 8) \tag{1}$$

where the subscript k stands for the regression equation number. In total, we have eight regression equations with adopter rated profit changes from adopting eight different PA technologies as dependent variables.

Y_k^* is the variable on the rated profit changes from adopting the k^{th} PA technology, which fall within one of the five intervals: (i) less than negative 10%, (ii) between negative 10% and negative 5%, (iii) between negative 5% and 5%, (iv) between 5% and 10%, and (v) above 10%. X_k is the set of independent variables, with their meanings explained in Table 1, β_k is the corresponding coefficient vector, and U_k is the error term with mean 0 and variance σ_k^2.

5. Data description

We asked farmers to rate their profit change after adopting each of the listed PA technologies, which include two geo-referencing technologies (auto-steering and ASC), two intra-field diagnosis technologies (satellite imagery and UAV remote sensing), and four application technologies (VR fertilizer, VR seed, VR pesticide and VR irrigation). Six options on profit change were provided, which included five options of rated profit change ('Reduced by >10%', 'Reduced by 5-10%', 'Little change (within 5%)', 'Increased by 5-10%' and 'Increased by >10%'). The sixth option ('no idea') was provided to accommodate respondents not aware of the degree of profit change yet. The dependent variables included in the models are adopters rated profit changes after adopting eight PA technologies.

The description of explanatory variables used in the interval regression models is provided in Table 1. We divided those explanatory variables into five categories, farm characteristics and management, farmer characteristics, information sources, farm soil characteristics, and weather and regional factors. For farm characteristics and management, we included cropland area, ownership, and conservation practice. Most studies found larger farms are more likely to adopt PA technologies (Tamirat et al., 2017; Schimmelpfennig and Lowenberg-DeBoer, 2020; Shang et al., 2021). Farm size was also found to influence the effects of various PA technologies on farm profit (Shockley

Table 1
Description of explanatory variables used in the interval regression models.

Category	Variable	Description	N	Mean (Std. Dev.)	Min	Max
Farm Characteristics and Management	Cropland acre	Total area of cropland (in 1000 acres)	1056	1.419 (1.608)	0.002	16
	Ownership	Proportion of owned cropland acres	1056	0.528 (0.329)	0	1
	Conservation Practice	Whether producers use conservation tillage and/or cover crops (0 = use none of the practice; 1 = use one of the practices; 2 = use both practices)	1080	1.208 (0.742)	0	2
Farmer Characteristics	Silent generation	Farmers born on or before 1945	1078	0.082 (0.274)	0	1
	Baby boomer	Farmers born between 1946 and 1964	1078	0.564 (0.496)	0	1
	Gen X	Farmers born between 1965 and 1980	1078	0.240 (0.427)	0	1
	Millennial and Gen Z	Farmers born on or after 1981	1078	0.114 (0.318)	0	1
	Education	Highest education level completed (1 = 'High school or less'; 2 = 'Some college, technical school'; 3 = '4-year college degree'; 4 = 'Advanced degree')	1095	2.089 (0.827)	1	4
Information sources	Agricultural consultants	Importance of agricultural consultants when making PA decisions (1 = 'Not important'; 2 = 'Slightly important'; 3 = 'Somewhat important'; 4 = 'Very important'; 5 = 'Extremely Important')	1074	3.061 (1.239)	1	5
	Machinery dealers	Importance of machinery dealers when making PA decisions (1 = 'Not important'; 2 = 'Slightly important'; 3 = 'Somewhat important'; 4 = 'Very important'; 5 = 'Extremely Important')	1074	3.130 (1.246)	1	5
Farm soil characteristics	Highly erodible land (HEL)	Percentage of cropland that is highly erodible land (1 = '0%'; 2 = '1–5%'; 3 = '6–10%'; 4 = '11–20%'; 5 = '21–30%'; 6 = '>30%')	1077	2.316 (1.554)	1	6
	Saline/sodic conditions	Percentage of cropland that has saline or sodic conditions (1 = '0%'; 2 = '1–5%'; 3 = '6–10%'; 4 = '11–20%'; 5 = '21–30%'; 6 = '>30%')	1034	2.001 (1.159)	1	6
	Perceived farm soil conditions	View on 'Not sure whether soil conditions on my farm will benefit from PA' (1 = 'Strongly disagree'; 2 = 'Disagree'; 3 = 'Neutral'; 4 = 'Agree'; 5 = 'Strongly agree')	1073	2.809 (0.915)	1	5
	Slope	Slope of the field (degree)	1118	2.743 (1.785)	0	15.301
	LCC12	Land Capability Class 1 and 2	1118	0.725 (0.258)	0	1
Weather factors	Precipitation	30-year average precipitation in millimeter (mm) (May–September)	1119	452.339 (60.777)	329.314	589.121
	Temperature	30-year average temperature in Celsius (May–September)	1119	18.793 (1.273)	15.589	21.616

et al., 2012; Velandia et al., 2013; Schimmelpfennig, 2016; Späti et al., 2021; McFadden et al., 2023). Thus, we included the cropland area variable to find the potential relationship between farm size and PA induced profit change. Ownership variable captures the percentage of owned cropland acres to total cropland acres. As land ownership ensures multi-year utilization of spatial data collected through PA technologies (Daberkow and McBride, 1998), it could enhance data interpretation and therefore positively affect profitability. Furthermore, positive correlation was also found between farmers' adoption status of PA and conservation practices (Schimmelpfennig, 2018; Kolady and Van Der Sluis, 2021). Therefore, we included conservation practice, which indicates producers' adoption status of no-till and cover crops, as an explanatory variable in the model to investigate their potential complementary effects towards PA profitability. In addition, it could take multiple years before PA technologies start to generate positive agronomic and economic benefits (Griffin, 2016). To capture profit change caused by different durations of PA usage, we included three dummy variables, namely 3–5 years, 6–10 years, and 10+ years, with <3 years as the baseline. Note that usage duration distributions are demonstrated in Fig. 2, as they vary across different PA technologies.

Among farmer characteristic variables, age plays an ambiguous role in PA usage decisions. Most literature findings show younger farmers are more likely to adopt PA technologies (Daberkow and McBride, 2003; Nair et al., 2011; D'Antoni et al., 2012; Tey and Brindal, 2012). This is likely because younger farmers are more technology-oriented and have longer planning horizons (Larson et al., 2008). However, older farmers generally have more farming experience and skills, thus are more capable at information interpretation (Vecchio et al., 2022). Following the examples of Griffin et al. (2020) and Ofori et al. (2020), we categorized farmers into four categories based on their birth years. Specifically, those who were born on or before 1945 is referred to as the Silent Generation, those born between 1946 and 1964 as Baby Boomers, those born between 1965 and 1980 as Generation X, and those born on or after 1981 as Millennial. There are also seven respondents born after 1996 that belong to Generation Z, whom we merged with the Millennial due to the small number of respondents. Possibly due to the complex nature of information intensive PA technologies, education has been found to be positively related to PA adoption decisions (Khanna, 2001; Roberts et al., 2002; Schimmelpfennig and Ebel, 2016). Therefore, investment in human capital through education could equip farmers with more capacity to learn and efficiently use these technologies, which may in return enhance PA profitability.

Regarding the importance of information sources, we examined the role of agricultural consultants and machinery dealers in adopters' perceived benefits. We hypothesize that adopters who consider those information sources as more important in making PA use decisions are more likely to experience profit increase. Due to the complexities of PA technologies, farmers generally need advice from external sources to best utilize them. The use of consultant service was found to be positively associated with yield map and VR fertilizer adoption (Robertson et al., 2012). While farmers have minimal reliance on expert guidance towards embodied knowledge PA technologies, they heavily rely on agricultural consultant in information intensive PA technologies for data interpretation, zone delineation and VR map generation. Local machinery dealers also provide farmers with a source of information on issues such as cost, service, as well as compatibility between components and brands (Andrade-Sanchez and Heun, 2010).

Soil quality and variability could affect the effectiveness of the technologies, and therefore the economic outcomes from adoption (Isik and Khanna, 2002; Isgin et al., 2008; Shang et al., 2021). Variation in topsoil depth, soil pH values, and pest infestation results in profitability change from VRT adoption (Wang et al., 2003). Compared to farms with higher soil quality, farms with lower soil quality are likely to be associated with higher gains in productivity due to adoption of soil testing and VRT (Khanna, 2021). As VRT allows varying the timing and rate of application in a targeted manner, it will particularly benefit the low-quality soil and soil with sufficient spatial variability (Khanna, 2021). To capture the soil quality and variation factors, we included five variables. Of those, three variables are survey data provided by farmers while two are from the public data source. Specifically, we asked farmers

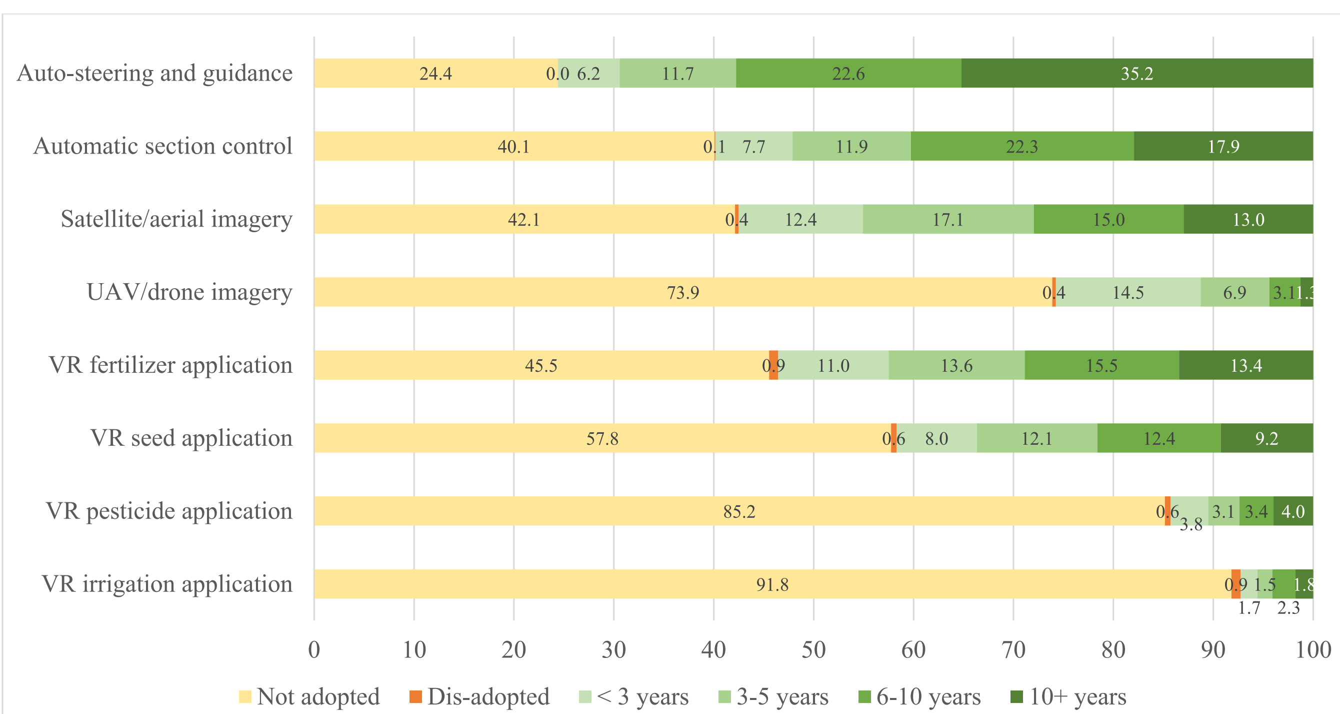

Fig. 2. Producer usage status of various PA technologies, based on 2021 Midwest farmer survey (Unit: percentage).
Note: The total number of responses for adoption status are 1099, 1088, 1087, 1091, 1087, 1084, 1085 and 1076 for auto-steering and guidance, automatic section control, satellite/aerial imagery, unmanned aerial vehicle (UAV)/drone imagery, variable rate (VR) fertilizer, seed, pesticide and irrigation application respectively.

about the percentages of their cropland under highly erodible conditions, percentages under saline/sodic conditions, as well as their agreement towards the statement 'not sure whether soil conditions on my farm will benefit from PA' (Table 1). The publicly available data that were used to represent soil quality were average land slope and percentage of soil belonging to land capability class (LCC) I and II. The former captures the degree of variability in the terrain and the latter characterizes the land suitability to produce cultivated crops. To capture the weather and regional factors, we collected average annual precipitation and temperature for the growing season (May to September) at the county level over the last 30 years (from 1991 to 2020).

6. Results and discussion

6.1. Adoption rates and usage years

Among all PA technologies, auto-steering and guidance has the highest adoption rate (76%) and the highest percentage (47%) of adopters (among all adopters) who have used the technology for >10 years. Most adopters of georeferencing technologies have used them for >6 years, with only 8% and 13% of farmers respectively who have used auto-steering and auto section control for <3 years (Fig. 2). These findings indicate that while the georeferencing technologies currently have the highest adoption rates among all PA technologies, their adoption rates stagnated in recent years.

Of the diagnostic technologies, nearly 60% farmers have adopted satellite imagery, with adopters evenly distributed across the usage duration provided. As a new technology, the adoption rate of UAV/drone imagery is relatively low at 26% with only 5% percent of adopters having >10 years of usage experience and 57% of adopters with <3 years of experience. A 2018 survey carried out in Missouri about 3 years prior to our survey also found only 8% of the respondents were UAV adopters (Skevas and Kalaitzandonakes, 2020). This indicates a substantial increase in UAV/drone imagery adoption rate in recent years.

Among the VRTs, the top two most adopted VR technologies are VR fertilizer (54%) and VR seed (42%) applications. In comparison, the adoption rates of VR pesticide and VR irrigation application are considerably lower at 14% and 7% respectively. One possible reason underlying the low adoption rate of VR pesticide is that pesticide only constitutes a small percentage of total input costs, therefore cost savings from VR pesticide adoption is not likely comparable to those of VR fertilizer and seeding. In our study region, most agricultural land is non-irrigated, which explains the lowest adoption rate of VR irrigation. For all VR technologies, the percentages of adopters who have used it for <6 years and those who used it for >6 years are similar, which indicates that the adoption rates of the VRTs have been steadily increasing over the years.

6.2. Profit change following PA adoption

Fig. 3 displays the profit changes following PA adoption. For each of the eight listed PA technologies, we documented the rated profit change by adopters and the perceived profit change by non-adopters.

For each of the listed PA technologies, approximately 60% of non-adopters indicated they had 'no idea', ranging from 56% for VR seed application to 63% for VR irrigation application (Fig. 3). This is not surprising since non-adopters have no direct hands-on knowledge on PA profitability, most of them likely have not received such information from indirect sources such as university extension and other farmers, or that they could not link such information with their own farms and

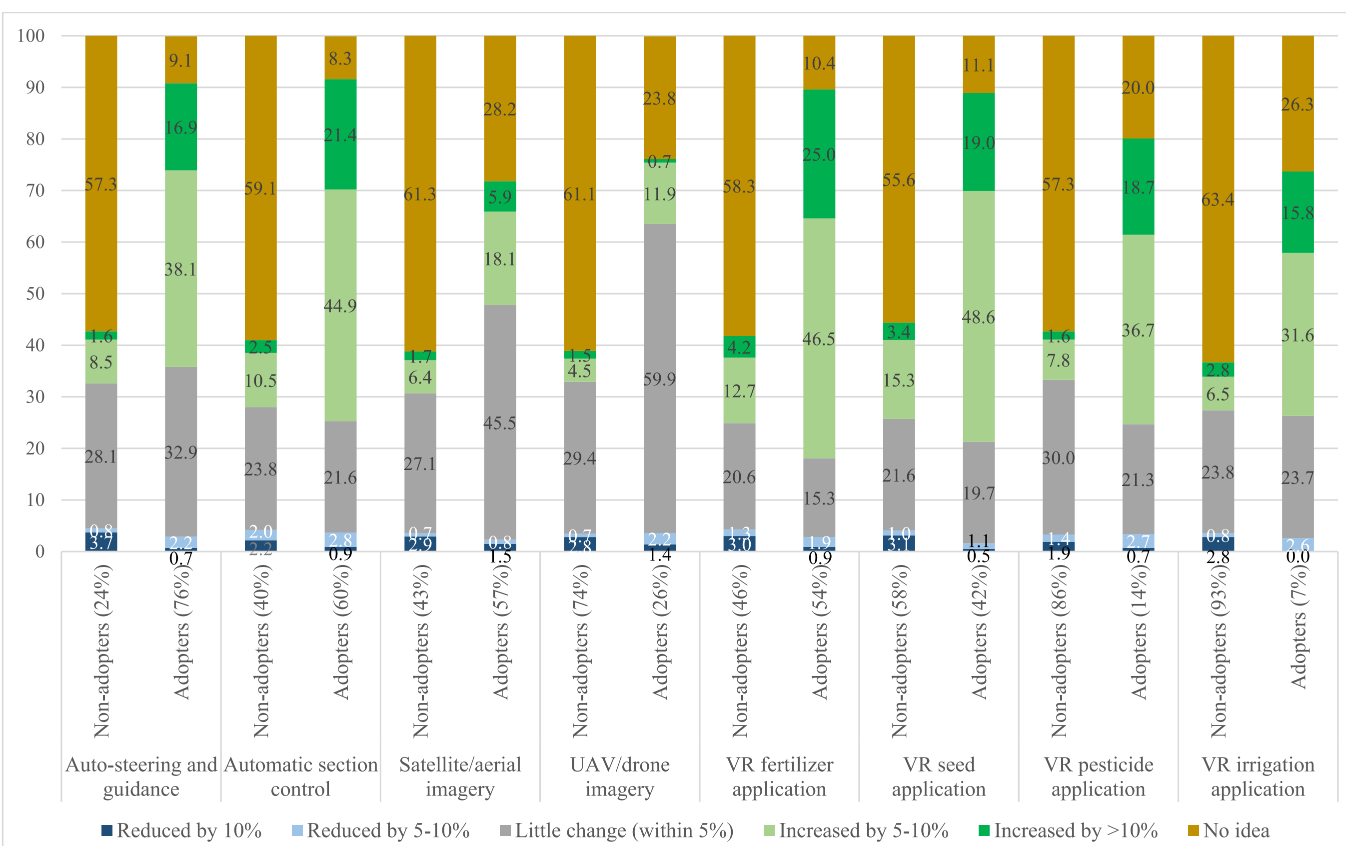

Fig. 3. Producer rated/perceived profit change after adopting various PA technologies, by adoption status.
Note: The total number of responses for profit change are 1068, 1056, 1044, 1035, 1054, 1037, 1044, and 1027 for auto-steering and guidance, automatic section control, satellite/aerial imagery, unmanned aerial vehicle (UAV)/drone imagery, variable rate (VR) fertilizer, seed, pesticide and irrigation application respectively.

regions due to the scarcity and case-specific research in this regard. This highlighted the need for a better understanding of PA generated profit change from adopters' experience over regions with different farm, soil, and weather characteristics.

Among adopters, only about 10% indicated an unawareness of the profitability towards auto-steering and guidance, automatic section control, VR fertilizer and seeding applications. Adopters are more likely to have no idea towards profitability of diagnostic PA technologies (28% for satellite imagery and 24% for UAV/drone remote sensing), as well as VR irrigation (26%) and pesticide (20%) technologies. Diagnostic technologies increase farm profit through increased VRT efficiency, it is therefore hard for farmers to separate their effects on profit. A breakdown by their years of adoption reveals that for all technologies, adopters who used it for <3 years were more likely to have no idea about the technology generated profit change (Table 2). As adopters accumulate more experience and data support over the years, they gain more understanding about the effect of PA adoption on their profit.

The top three PA technologies rated by most adopters that achieved at least a 5% increase in profitability are VR fertilizer application (72%), VR seed application (68%), and automatic section control (66%). Interestingly, the top three technologies perceived by most non-adopters as achieving at least a 5% increase in profitability coincide with the ratings of adopters, except that percentages of non-adopters are much lower: VR seed application (19%), VR fertilizer application (13%), and automatic section control (13%). The correspondence between non-adopters and adopters' answers towards the top three most profitable technologies indicate the potential influence of adopters' opinions towards the perceptions of some non-adopters.

6.3. *Summary statistics of explanatory variables*

Table 1 also presents the summary statistics for all the modeled variables based on responses from all farmers. The cropland area averaged 1419 acres across all four states. To check the representativeness of our survey sample, we compared the survey data with agricultural census data regarding farm size under different tenure status, using *t*-test (Table 3). Overall, the average farm sizes for NE and SD, at 1106 and 1566 respectively, are not statistically different from the land acre values of 1000 and 1469 acres reported by the 2022 State Agriculture Overview for these two states. Yet farm sizes for MN and ND are considerably larger than the census data at a statistically difference level of 1%. A breakdown of farms by tenure status further reveals that for the full owner category, the survey average sizes are statistically higher than the census averages for MN and ND. For part owners, which represent the majority of survey sample, our survey average farm sizes are statistically smaller than the census averages for NE and SD, yet farm size for MN is statistically smaller than the census average. No statistical difference in farm acres is observed for the tenant category for all studied states. The average number of conservation practices is 1.208, which means that on average farmers have adopted at least one practice out of conservation tillage and cover crops.

Regarding generation categories, Table 1 shows that the majority (56.4%) of our respondents are baby boomers, followed by Generation X (24.0%). The rest categories, Millennial and Generation Z (11.4%) and Silent Generation (8.2%), together account for <20% of the respondents. Compared to the Kansas farm operators as of 2018 (Griffin et al., 2020), the percentage of the Silent Generation operators, as indicated in our 2021 survey, has declined by about 10%, indicating that many of the Silent Generation have exited farm management. Meanwhile, the percentage of Generation X has slightly increased. Compared to Griffin et al. (2020), we also found more Baby Boomers responding to our survey, which probably reflects a regional difference. Similar to Ofori et al. (2020), we also set Baby Boomer as a reference group in the regression models as most farmers belong to this generation. The average value for education is 2.089, implying that on average farmers have completed some college or technical school. The average values for agricultural consultants and machinery dealers are 3.061 and 3.130 respectively, indicating that both sources are considered by farmers as

Table 2
Adopter rated profit change due to PA adoption, by usage years (Unit: percentage).

		Reduced by >10%	Reduced by 5–10%	Within 5%	Increased by 5–10%	Increased by >10%	No idea
Auto-steering and guidance	< 3 years	2.9	8.8	36.8	25.0	5.9	20.6
	3–5 years	0.0	1.6	43.3	39.4	7.1	8.7
	6–10 years	0.8	1.6	30.9	41.1	16.7	8.9
	10+ years	0.5	1.6	30.2	38.1	22.3	7.4
Automatic section control	< 3 years	0.0	2.4	32.9	39.0	4.9	20.7
	3–5 years	0.8	4.8	29.6	40.8	15.2	8.8
	6–10 years	0.8	2.5	15.7	52.9	21.5	6.6
	10+ years	1.6	2.1	18.9	39.8	33.0	4.7
Satellite/aerial imagery	< 3 years	0.8	0.8	43.9	15.9	3.0	35.6
	3–5 years	1.7	1.1	51.4	13.8	3.3	28.7
	6–10 years	1.9	1.2	47.2	19.3	3.7	26.7
	10+ years	1.4	0.0	37.9	24.3	14.3	22.1
UAV/drone imagery	< 3 years	1.3	1.3	58.1	10.3	0.7	28.4
	3–5 years	2.7	4.1	70.3	8.1	0.0	14.9
	6–10 years	0.0	2.9	47.1	23.5	2.9	23.5
	10+ years	0.0	0.0	57.1	21.4	0.0	21.4
VR fertilizer application	< 3 years	1.7	2.5	21.9	44.5	11.8	17.7
	3–5 years	0.0	3.4	19.2	48.6	21.2	7.5
	6–10 years	1.2	0.6	12.1	45.5	28.5	12.1
	10+ years	0.7	1.4	9.6	47.3	35.6	5.5
VR seed application	< 3 years	0.0	1.2	25.6	45.4	7.0	20.9
	3–5 years	0.0	1.5	27.7	49.2	13.1	8.5
	6–10 years	0.8	0.8	13.9	49.2	23.1	12.3
	10+ years	1.0	1.0	13.0	50.0	31.0	4.0
VR pesticide application	< 3 years	0.0	7.3	24.4	24.4	14.6	29.3
	3–5 years	0.0	0.0	26.5	50.0	8.8	14.7
	6–10 years	0.0	0.0	16.7	36.1	22.2	25.0
	10+ years	2.4	2.4	17.1	39.0	26.8	12.2
VR irrigation application	< 3 years	0.0	5.6	11.1	27.8	11.1	44.4
	3–5 years	0.0	6.3	43.8	43.8	0.0	6.3
	6–10 years	0.0	0.0	28.0	40.0	4.0	28.0
	10+ years	0.0	0.0	11.1	11.1	50.0	27.8

Table 3
Comparison of survey responses with census data regarding farm acres.

State	Full owner		Part owner		Tenant		Overall	
	Census	Survey	Census	Survey	Census	Survey	Census	Survey
MN	144	432***	788	1043***	395	616	377	902***
NE	452	512	1760	1295***	819	681	1000	1106
ND	464	846***	2733	2590	1124	1902	1512	2416***
SD	664	730	2542	1782***	1110	1440	1469	1566

Note: Census values for land acres for full owner, part owner and tenant are from 2017 Census of Agriculture. The census value for overall land acres are from 2022 State Agriculture Overview. *, **, and *** indicates that survey data is significantly different from census data at $p < 0.10$, $p < 0.05$, and $p < 0.01$ based on t-test.

somewhat important in making PA decisions.

The average values of highly erodible land and saline/sodic conditions are 2.316 and 2.001 respectively, which imply that on average farmers have between 1 and 5% of their croplands with such land conditions. Perceived farm soil conditions averaged 2.809, which indicates that on average farmers shows disagreement towards the statement that "not sure whether soil conditions on my farm will benefit from PA", or that farmers in general believe their farm soil conditions will benefit from PA. On average, fields with soil types of LCC I and II take 72.5%, indicating that most of the fields have no or few limitations for crop cultivation. The land slope in our study ranges from 0 to 15.301% with a mean value of 2.743%.

The 30-year county average growing-season precipitation spanned from 329.314 to 589.121 mm, and the average temperature fell between 15.589 and 21.616C degrees in our study region. Precipitation follows an east-west declining pattern while the temperature exhibits a south-north declining gradient. This indicates a great variation in precipitation and temperature, which potentially affects farm productivity and farmer decision-making.

Table 4
Interval regression estimation results for rated profit change after adoption of various PA practices.

Category	Technologies	Georeferencing		Intra-field diagnosis		Application		
	Variable	Auto-steering	ASC	Satellite Imagery	UAV/ Drone	VR Fertilizer	VR Seed	VR Irrigation
Farm Characteristics and Management	3–5 years	2.542**	0.562	−0.634	−0.764	0.754	−0.101	−1.87
		(0.987)	(0.971)	(0.785)	(0.787)	(0.764)	(0.754)	(2.625)
	6–10 years	3.217***	1.939**	−0.389	2.803***	2.036***	1.284	−1.794
		(0.924)	(0.892)	(0.814)	(1.021)	(0.766)	(0.783)	(2.104)
	10 + years	3.579***	2.352**	2.588***	2.17	2.547***	1.536*	8.148***
		(0.917)	(0.929)	(0.844)	(1.569)	(0.822)	(0.832)	(2.445)
	Cropland acre	0.064	−0.029	−0.172	−0.195	−0.027	−0.125	−0.454*
		(0.135)	(0.142)	(0.142)	(0.149)	(0.161)	(0.142)	(0.235)
	Ownership	−0.245	−1.477	−1.102	0.424	1.984**	0.051	1.946
		(0.768)	(0.898)	(0.996)	(1.241)	(0.920)	(0.905)	(2.906)
	Conservation Practices	0.303	0.163	−0.057	−0.238	0.774**	0.735*	−1.279
		(0.325)	(0.385)	(0.420)	(0.505)	(0.392)	(0.391)	(1.581)
Farmer Characteristics	Silent Generation	−0.059	−0.908	1.404	−1.164	−0.333	1.811	3.151
		(1.159)	(1.359)	(1.305)	(1.911)	(1.236)	(1.236)	(2.787)
	Gen X	−0.625	−0.217	−1.282*	−1.298	−0.156	−0.299	1.022
		(0.520)	(0.596)	(0.668)	(0.863)	(0.642)	(0.640)	(2.314)
	Millennial and Gen Z	−0.144	1.381*	−1.908**	−1.745*	−0.004	0.186	−4.711**
		(0.663)	(0.770)	(0.827)	(0.997)	(0.788)	(0.763)	(2.382)
	Education	0.12	0.114	0.235	−0.175	0.455	0.541	0.574
		(0.286)	(0.327)	(0.345)	(0.458)	(0.331)	(0.333)	(0.886)
Information Resources	Agricultural consultants	0.413*	0.517**	0.837***	0.34	0.436*	0.545**	−0.81
		(0.214)	(0.246)	(0.275)	(0.355)	(0.262)	(0.256)	(0.606)
	Machinery dealers	0.724***	0.594**	0.148	−0.028	0.16	0.585**	−0.378
		(0.219)	(0.253)	(0.273)	(0.350)	(0.241)	(0.264)	(0.678)
Soil Characteristics	HEL	0.226	0.107	0.068	0.154	0.014	0.072	−1.945***
		(0.173)	(0.200)	(0.212)	(0.293)	(0.204)	(0.209)	(0.531)
	Saline/sodic conditions	0.307	0.127	0.231	0.178	0.904***	0.344	0.858*
		(0.215)	(0.244)	(0.258)	(0.331)	(0.273)	(0.255)	(0.457)
	Soil conditions	−0.251	−1.057***	−0.187	−0.277	−0.778***	−0.753***	−1.528*
		(0.242)	(0.275)	(0.283)	(0.366)	(0.281)	(0.280)	(0.876)
	Slope	0.108	0.437**	−0.053	0.515**	0.429**	−0.008	0.491
		(0.165)	(0.189)	(0.207)	(0.236)	(0.201)	(0.187)	(0.493)
	LCC12	1.418	−0.641	−0.96	1.712	0.831	−1.37	−9.841***
		(0.991)	(1.090)	(1.218)	(1.463)	(1.150)	(1.122)	(2.659)
Weather Factors	Precip	−0.004	0.002	−0.005	0.008	0.009*	−0.003	0
		(0.004)	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.027)
	Temp	−0.323	−0.455*	0.069	−0.989***	−0.175	0.099	−0.93
		(0.208)	(0.237)	(0.252)	(0.324)	(0.244)	(0.245)	(0.688)
		4.443	10.507**	1.737	13.658**	−1.191	1.56	41.092**
	Constant	(4.191)	(4.834)	(5.206)	(6.781)	(5.189)	(5.085)	(15.981)
	Obs.	626	499	386	185	436	341	46
	LR Chi2	74.49	75.00	49.81	41.79	52.34	48.81	56.87
Model Fit Statistics	Prob > Chi2	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001

Note: *, **, and *** represent $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively. Standard errors are presented in the bracket under each of the estimated values.

6.4. Interval regression model findings

Table 4 displays the estimation results of eight interval regression models with adopter rated profit changes for eight PA technologies as dependent variables. As our dependent variables are the percentage of change in PA profitability, the estimated coefficient values also stand for the change in percentage point(s) with the positive value indicating an increase in percentage points and negative value indicating a decrease, when the independent variables increase by one unit. Except for VR pesticide model, all models all have chi-square calculated value greater than the chi-square critical value at 1% significance level, which means that the selected variables explain the variation of the rated profit changes after adoption of PA practices. However, we did not successfully locate any variable that could explain the variation of profit change for VR pesticide usage, thus did not display its model estimates in Table 4.

For all seven significant models, we can see that adopters with longer usage years reap higher profits from the PA technologies. For example, compared with auto-steering adopters of <3 years (baseline), the profit change experienced by adopters of 3–5 years, 6–10 years, and 10+ years increased by 2.542, 3.217 and 3.579 percentage points respectively. For the rest of PA technologies, we find the profit change rated by adopters of 3–5 years were not significantly different from those who used for <3 years. Compared to the VR fertilizer adopters of <3 years, the rated profit change by adopters of 6–10 years and 10+ years increased by 2.036 and 2.547 percentage points respectively. Table 4 findings suggest a long-period (over 10 years) of profit accruement for VR technologies, which could be due to a learning effect over time. Factors that enhance profitability also include improved information and interpretation from data collection over multiple years, as well as more experience in managing within-field variability (Castle, 2016). Similarly, we found that land ownership promotes a positive profit change from VR fertilizer adoption. Compared to tenant operated farm, full owner reported a profit increase by 1.984 percentage points, which is likely attributable to enhanced data interpretation on owned land (Daberkow and McBride, 1998).

Farmers who use conservation practices along with PA practices are more likely to find VR fertilizer and VR seed applications profitable. When farmers adopt one of the conservation practices (conservation tillage or cover crops), the rated change in profitability for VR fertilizer and seeding will increase by 0.774 and 0.735 percentage points, respectively. Likewise, the rated profitability change for VR fertilizer and seeding will increase by 1.548 (0.774 × 2) and 1.470 percentage points respectively if farmers adopt both conservation practices. This finding suggests a potential complementary effect between soil conservation practices and VRTs, which helps boost farmers' profit in VR fertilizer and seeding applications. PA technologies facilitate the adoption of conservation practices. Schimmelpfennig (2018) pointed out that PA usage could promote usage of conservation practices such as no till. As the targeted goals for both PA technologies and conservation practices are to promote economic sustainability and reduce negative environmental impact, farmers aiming to achieve such goals are likely to adopt them simultaneously.

Regarding the role of generation, we found that the Silent Generation and Generation X generally share similar views with Baby Boomers on the profitability of PA technologies. The only exception is the satellite imagery, which Generation X found less profitable compared to Baby Boomers. Compared to Baby Boomers, Millennials are less likely to find remote sensing technologies (satellite and drone) and VR irrigation profitable, yet more likely to find ASC profitable. Previous literature has found a negative correlation between age and adoption of high technologies as younger operators are more willing to embrace innovations and adopt information technology for farm management (Daberkow and McBride, 2003; Isgin et al., 2008; D'Antoni et al., 2012; Ofori et al., 2020). However, younger farmers generally have not accumulated as much wealth as older farmers (D'Antoni et al., 2012). Therefore, among the adopters, older farmers may find PA technologies more profitable. In our case, profit change ratings by Millennials in general are not as positive as Baby Boomers, probably due to their financing burden for PA investment or service costs.

Farmers who use agricultural consultants and machinery dealers are more likely to find increase in profitability following adoption of georeferencing technologies, as well as VR seed technologies. For example, when the importance level of machinery dealers increases by 1 unit, then the rated profitability change of VR seed technologies will increase by 0.585 percentage point. In addition, agricultural consultant plays an important role in boosting farmers' ratings on profit change regarding diagnostic technologies (satellite imagery) and VR fertilizer.

Farm soil conditions also play a key role in PA profitability. For example, profit change in VR irrigation was significantly affected by the percentage of highly erodible land on the farm. Specifically, when the percentage of highly erodible land increases by 1 unit (e.g., from 0% to 1–5%), the profit change on VR irrigation will be reduced by 1.945 percentage point. One possible reason for this finding is that irrigation induced erosion could reduce crop yield potential, especially for highly erodible land, which will compromise crop productivity and farm profit (Koluvek et al., 1993).

Similar to Schimmelpfennig and Lowenberg-DeBoer (2020), who showed VRT are more likely adopted on farms with higher soil variability, we found variability in saline and sodic conditions positively influence farmer perceived profit change. Specifically, when the percentage of saline and sodic land increases by 1 unit (e.g., from 0% to 1–5%), the profit changes after adoption of VR fertilizer and VR irrigation increased by 0.904 and 0.858 percentage points, respectively. Evaluation of spatial variability in soil salinity and sodicity is the prerequisite for VR technology. Through such information, VRT will help save input costs (fertilizer and water) through site-specific input application and therefore improve farm profitability (Günal, 2021). With increased portion of land affected by saline and sodic conditions, farmers are likely to find site-specific management that optimize input use more valuable. In contrast, if adopters are more uncertain about whether their farm conditions will benefit from PA, their ratings on profit change from the usage of ASC and all VR technologies will be negatively affected.

As discussed in McFadden et al. (2023), farm operators tend to adjust inputs accordingly in fields with greater slopes, in alignment with the zone management concept. We found farmers with steeper sloped fields more likely to observe profit increases from usage of ASC, drone, VR fertilizer, and VR irrigation. ASC contributes to more efficient input usage and helps reduce input cost, thus would be more beneficial for farms characterized by uneven topology. Similarly, one of the primary benefits for using drone in agriculture is to access areas that are difficult to reach, such as steep slopes. Soils on the sloped field are prone to runoff, especially at the bottom of hill where subsurface flow converges, which will further result in high nutrient losses (Easton and Petrovic, 2005). Therefore, site-specific usage of fertilizer becomes more necessary on higher sloped land. Uneven field elevation can also result in varying distribution of soil water content, forming dry zones in high-elevation portions of the field and ponding in low-elevation portions (Yari et al., 2017). Therefore, the steeper sloped fields will benefit more from VR irrigation application.

Table 4 results also indicate that farmers who farm in land with a higher percentage of LCC I & II are less likely to benefit from the VR irrigation technology. This finding is consistent with that of Khanna (2021), which also shows that farms with higher soil quality are less likely to see productivity gains due to adoption of VRT. This is probably because higher quality soil provides better growing conditions without utilizing VR irrigation and therefore lacks room for further productivity improvement.

Our survey spans crop production areas across four states (Fig. 1) and provides sufficient differentiations on precipitation (east-west gradient) and temperature (north-south gradient), which ranges from 329 to 589 mm for growing season precipitation and from 16 to 22C degrees for growing season temperature. As precipitation increases, VR fertilizer usage are rated as more profitable. When saturated with excess precipitation, soil will become more prone to runoff (Easton and Petrovic, 2005). Excessive chemical fertilizer that cannot be absorbed by plant will be left in the soil (Singh et al., 2020). Therefore, the chances for nutrient losses will increase with higher amount of precipitation and the washed away fertilizer will end up in water bodies, which result in water pollution. Therefore, the optimal application of fertilizer using VRT will be more beneficial in regions with greater precipitation level. We also found temperature increase negatively affects adopter rated profitability for ASC and UAV remote sensing, indicating that farmers in regions with lower temperature are more likely to rate these two technologies as profitable.

7. Conclusion

While profit is a most important consideration prior to new technology adoption, most of the non-adopters of different PA technologies had no idea how their profit would change following adoption, according to our survey responses from U.S. farmers in four states along the western margins of the U.S. Midwest. This highlights the necessity of investigating adopter rated profit change towards different PA technologies. Our paper compared adopters' rated profit changes for a range of PA technologies across different types of farmers and farms, as well as regions with heterogeneous soil and weather characteristics, to help non-adopters gain a better understanding of the potential PA benefit on their farm, thereby making more educated adoption decisions.

We found adopter rated profit changes due to PA adoption vary considerably across different PA technologies. The top three most profitable PA technologies rated by farmers are VR seed application, VR fertilizer application and automatic section control. About two thirds of adopters rated that these three technologies achieved at least a 5% increase in profitability. Our results also demonstrate a learning effect for PA technologies, which means that the profit from PA usage will increase over the years. In comparison to new adopters, more experienced PA adopters are more likely to see a noticeable change on profit. While the learning curves for embodied-knowledge technologies such as autosteering and guidance systems are generally short, most information intensive technologies like VRTs have long learning curves and it could take >10 years to fully reap the benefit. To facilitate PA adoption, it would be helpful to 1) provide financial support for the first a few years of adoption and 2) to promote connection opportunities among farmers so that the long-term adopters of PA technologies could share their experiences.

We also investigated factors that could potentially affect the ratings on PA profit change. Usage of conservation practices, such as conservation tillage and cover crops, was found to positively affect adopters' rated profit change for VR fertilizer and VR seed. This suggests a potential complementary effect between soil conservation practices and VRTs. Therefore, promoting simultaneous adoption of conservation practices and PA technologies could help agricultural enterprises better achieve environmental and economic goals. External information sources, such as consultants and machinery dealers, also helped adopters achieve greater profit increase.

Soil conditions and variability were found to play an important role in PA induced profit change. Specifically, we found that fields with a higher percentage of erosion and sodic/saline conditions were more likely to benefit from VR adoption. While farmers with higher soil quality are more likely to adopt PA due to their higher sales value, the farmers with lower soil quality are more likely to see a profit increase. Beyond soil factors, precipitation and temperature conditions also affected PA profitability. Therefore, profitability of PA technologies may differ across regions. It would be helpful to evaluate the effectiveness of different PA technologies based on soil and weather characteristics, and tailor the promotion efforts accordingly.

Overall, we found the benefit of PA from the profitability perspective promising. When compared with the very modest profit increase potential estimated by other research, the more optimistic ratings of PA profit change by adopters suggested that there could be multiple channels to reap PA profit. Rising input costs in recent years, further highlight the importance of using PA technology since its site-specific management help improve input use efficiency and, in many cases, reduce input cost.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

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