



Determinants of adoption and adoption intensity of precision agriculture technologies: evidence from South Dakota

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Abstract

Precision agriculture technologies (PATs) are promoted as part of both economically efficient and environmentally sustainable agriculture practices. Available PATs are generally classified into two groups; namely, embodied-knowledge and information-intensive PATs. Adoption levels of embodied-knowledge PATs are high relative to information-intensive PATs. Previous studies on the adoption of PATs do not differentiate between embodied-knowledge and information-intensive PATs. Additionally, most studies focus on the adoption of one or two of the available PATs rather than on adoption intensity—defined as the total number of individual PATs adopted. This study fills this gap in the literature by focusing on PAT adoption in general, and adoption intensity of embodied-knowledge and information-intensive PATs in particular. The study uses data from 198 farm-operator respondents in eastern South Dakota from a 2017 survey and employs descriptive statistics and probit and Poisson regression models for the analyses. As per the study, GPS guidance, yield monitor, and automatic section control systems are the most popular PATs, each with adoption rates of over 50%. Overall, findings from the study show that the effect of cropland size, producers' perceptions of profitability, and operator off-farm income are similar for both adoption and adoption intensity of embodied-knowledge and information-intensive PATs. However, there are differences in the effect of land productivity and familiarity with computer use between adoption and adoption intensity and between embodied-knowledge and information-intensive PATs. The effect of producers' perception of the environmental benefits of PATs is inconclusive and needs to be investigated in future research. The results indicate that analyzing PATs as a group of technologies masks differences in determinants between embodied-knowledge and information-intensive PATs. The study provides insights for developing programs, policies, and outreach efforts that encourage the adoption and adoption intensity of both embodied-knowledge and information-intensive PATs. Findings from the study will also be of interest to precision agriculture researchers, extension personnel, agribusinesses, and policymakers who may consider PATs as tools for improving agricultural sustainability and food security.

Keywords Embodied-knowledge technology · Information-intensive technology · Precision agriculture · Adoption intensity · Adoption bundles

Introduction

In recent years much attention has been paid to soil health, water quality, and long-term sustainability of agricultural production globally. Declines in the quality and quantity of natural resources, a changing climate, and volatile input and commodity prices challenge the economic sustainability of agricultural production systems. Approaches to addressing the negative environmental and ecosystem impacts of agriculture while ensuring long-term economic sustainability and food security include the adoption of precision agriculture technologies (PATs).

The International Society of Precision Agriculture (ISPA 2018) defines precision agriculture as: “a management strategy that gathers, processes and analyses temporal, spatial and individual data and combines it with other information to guide site, plant or animal specific management decisions to improve resource efficiency, productivity, quality, profitability and sustainability of agricultural production.” Many agricultural producers utilize this data-driven technology as they seek to optimize the amounts, precise locations, and timing of applying seeds, fertilizers, and herbicides to their fields, with the aims of improving input utilization, increasing crop output and optimizing profits (Tey and Brindal 2012; Chen et al. 2009). PAT allows producers to conserve inputs and thus improve efficiencies while maintaining or even improving output, and ultimately enhancing profitability (Deutz 2018).

Profitability and economic significance of the adoption of PATs vary based on the size of management zones, variations within management zones, field shapes, soil fertility status, costs and prices, and types of PATs used (Robertson et al. 2008, 2012; Shockley et al. 2012, 2018). The adoption of PATs requires substantial investment of capital (Schimmelpfennig and Ebel 2011; Schimmelpfennig 2016; Tozer 2009). Profitability increases associated with the adoption of PATs assume that net savings made from any precision application via cost-saving from reduced input usage and or revenue enhancements due to yield gains more than offset the costs of specialized equipment (capital) and any additional labor. Consequently, the available evidence on the profitability of PATs is mixed (Tey and Brindal 2012).

The adoption of PATs has on-farm private consequences in terms of their potential to reduce costs and increase yields and profits, as well as off-farm public benefits such as improved soil, water, and air quality—particularly in intensive agriculture production areas. For example, site-specific management and application of nutrients needed for crops to reach their maximum potential yield could reduce nutrient contamination in groundwater and downstream water sources (Khanna and Zilberman 1997; Sylvester-Bradley et al. 1999; Reichardt and Jürgens 2009; Tey and Brindal 2012). This aspect of PAT is very important since agricultural non-point source pollution is a major contributor to contamination of the worlds’ waterways (Carpentier et al. 1998; Hudson et al. 2005). Unlike their financial returns, PATs’ environmental benefits tend to be more abstract or realized over the longer term.

It is clear from the brief review presented above that the evaluation of costs and benefits of using PATs is complicated. Also, the availability of several types of PATs make producers’ decisions on adopting PATs a complex process. Based on the specialized skills required by the end-user to fully utilize the technology, PATs have been categorized into the following two groups: (i) embodied-knowledge technologies, and (ii) information-intensive technologies (Griffin et al. 2004; Barnes et al. 2019). For embodied-knowledge technologies, the value of the technologies is embodied within them and the end-user does

not require any special skills to fully utilize them, so their adoption can directly increase efficiency or productivity as soon as they are used (Robertson et al. 2012). Examples of embodied-knowledge PATs include automatic section control and auto-guidance systems. Unlike embodied-knowledge technologies that are relatively simple and easy to use, information-intensive technologies are those that generate a large amount of data and information and the end-user needs specialized skills to interpret and fully utilize the data and information for farm and business management purposes. Examples of information-intensive technology include yield monitors and variable-rate systems that enable the automated applications of fertilizer, seeds, and chemicals to a given area.

Studies from the United States, Canada, Australia, and the EU show that PAT adoption varies by technology type and region/countries (Griffin et al. 2004; Erickson et al. 2017; Miller et al. 2019; Mitchell et al. 2018; Robertson et al. 2012; Tamirat et al. 2018; Michels et al. 2020; Paustian and Theuvsen 2017). Some studies show that adoption rates of information-intensive PATs are lower than those of embodied-knowledge PATs (Miller et al. 2019; Erickson et al. 2017; Mitchell et al. 2018; Robertson et al. 2012; Bramley and Ouzman 2019; Bullock and Lowenberg-DeBoer 2007). For example, auto guidance was used in 59% of crop area planted to corn in the United States in 2016, and by 77% of grain growers in Australia in 2012, whereas variable-rate technology (VRT) fertilizer was used in 29% of crop area planted to corn in the United States in 2016 and among 49% of grain growers in Australia in 2012 (Lowenberg-DeBoer and Erickson 2019).

Although PAT adoption rates have increased since 1997, the overall U.S. adoption rate is less than 50% of planted crop area (Schimmelpfennig 2016). Previous studies on PAT adoption in the United States link variation in adoption behavior to a large number of factors such as farm and farmer characteristics (age, education, farm size, etc.), profitability potential, market conditions, labor scarcity, and cost of the technology (Miller et al. 2017, 2019; Schimmelpfennig 2016; Lambert et al. 2015; Isgin et al. 2008; Pierpaoli et al. 2013). Other studies report evidence of the bundling of PAT adoption (Lambert et al. 2015). Using farm-level panel data from Kansas, Miller et al. (2019) showed that the adoption of bundles of information-intensive PATs is contingent on prior adoption of embodied-knowledge PAT and/or information-intensive PATs, suggesting that producers tend to adopt technologies that are relatively easy and simple to use first. For example, GPS guidance systems with automatic control for fertilizer/chemical applications were used by 78% of crop input dealers in the United States, followed by automatic sprayer boom sections at 73% in 2017 (Erickson et al. 2017). However, studies that investigate the determinants of adoption and adoption intensity of embodied-knowledge and information-intensive PATs and the relationship between these adoption decisions are lacking.

The objectives of this study are twofold, to examine the determinants of: (i) the adoption of embodied-knowledge and information-intensive PATs in the United States, and (ii) the adoption intensity (defined as the total number of individual PATs adopted) of embodied-knowledge and information-intensive PATs in the United States. More specifically, this study examines whether the determinants of adoption and adoption intensity vary between embodied-knowledge and information-intensive PATs.

This study contributes to the existing literature on the adoption of PATs in the following ways. To the best of authors' knowledge, this is the first survey-based study from the U.S. Midwest that analyzes the determinants of adoption and adoption intensity of embodied-knowledge and information-intensive PATs, separately. By examining the characteristics and attitudes among producers who did and did not adopt the two different PAT types, this study informs future programs and policies that seek to scale up adoption and diffusion of PATs. An improved understanding of the determinants of adoption and adoption intensity

will give insights on tailoring policies, programs, and outreach efforts aimed at increasing not only adoption but also adoption intensity of PATs, particularly of information-intensive technologies.

Materials and methods

Data

This study focuses on South Dakota, a state in the U.S. Midwest, a region generally referred to the set of states consisting of Illinois, Indiana, Iowa, Kansas, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, South Dakota, and Wisconsin. The area is known for its fertile land and agricultural prominence, it contains about 63% of the usable cropland in the United States, and about 75% of the area's cropland is planted to corn and soybeans. The remaining 25% is used for the production of a variety of other crops, including alfalfa, small grains, and horticultural products (USDA 2020). The U.S. Midwest is a region with large farms, where PAT adoption and implementation has the potential to contribute to on-farm economic and environmental benefits and off-farm benefits, such as ecosystem protection, by reducing non-point source water pollution. Understanding the determinants of adoption and adoption intensity of PATs in a U.S. Midwest setting will be of value to agribusinesses in developing appropriate marketing strategies and outreach efforts. Furthermore, it will provide insights to policymakers in formulating policies and programs to scale up the adoption of PATs in efforts to address the potential negative environmental and ecosystem effects of intense agricultural production in the region without compromising agricultural productivity and economic profitability.

Among Midwestern states, agriculture's share of the state economy is the highest (~30%) in South Dakota (Mercier 2014). The Missouri River divides the state into similar-sized areas: the eastern part of the state has relatively productive farmland with generally sufficient rainfall levels to enable row crop production, whereas the western part is comparatively arid with soils that are largely unsuitable for row crop production. In eastern South Dakota, a rotation of corn and soybeans represents the predominant crop production system. Since eastern South Dakota is the most intensely-cropped area in the state and most of the available PATs are targeted toward crop production, this study focuses on the adoption of PATs in eastern South Dakota. In particular, the data used for this study comes from a farm-level survey conducted in eastern South Dakota in Spring 2017.

The project team purchased a list addresses of corn, soybean, and wheat growers in eastern South Dakota from the marketing and publishing company Penton Agriculture, which maintains a comprehensive list of row crop producers in the U.S. Midwest. The research team employed stratified random sampling to select a representative sample of corn, soybean, and wheat farm operators from the major corn, soybean, and wheat-producing counties in eastern South Dakota. The study participants were chosen from a list of the top 10 corn, soybean, and wheat-producing counties in eastern South Dakota. For corn and soybeans, the top 10 counties coincided, the top ten wheat-producing counties included four overlapping counties with the top-ten corn and soybean-producing counties and six additional counties. Because very small farms are relatively unlikely to adopt PATs, a minimum farm size of 32.4 hectares (80 acres) was used as a screening criterion for the study participants. Participants were then selected randomly from these counties. To have a balanced cross-section of producers, 800 participants were designated toward the top corn and

soybean-producing counties and 400 participants towards the top-producing wheat counties. Using this method allowed for some overlapping responses from wheat producers in the top corn and soybean-producing counties, while increasing the response rate of wheat producers overall.

In January 2017, a total of 1200 surveys were mailed to the randomly selected producers described above. The project team contacted the study participants in three rounds: (1) an invitation letter describing the survey, a hard copy of the survey, and return envelopes were mailed to all study participants; (2) a reminder postcard was mailed to all survey participants after 2 weeks of the initial mailing; and (3) a hard copy of the survey with return envelopes were mailed to the remaining non-respondents three weeks after mailing reminder postcards. Of the 1200 surveys mailed out, 37 were returned to the sender, 59 were returned with insufficient data, and 198 were returned with usable data for most of the questions, resulting in an overall response rate of 18%. For context, response rates of the U.S. Department of Agriculture's (USDA) National Agricultural Statistic Service (NASS) surveys are on the decline, particularly in Midwestern states (Johansson et al. 2017). Declining response rates are attributed to factors such as increased usage of survey methods by academics and marketers, and the growing number of survey requests that producers receive (Johansson et al. 2017; Rogelberg and Stanton 2007).

The survey collected data on farm and farmer characteristics, producers' perceptions on costs and benefits of PATs, details on production practices, and adoption levels of PATs. The survey also collected adoption data on three embodied-knowledge PATs (autosteer, GPS guidance, and automatic section control (shut-offs)) and six information-intensive PATs (yield monitor, variable-rate systems, grid soil sampling, prescription field maps, aerial/satellite imagery, and crop tissue sampling). A brief description of each of the PATs included in the study is provided in the Appendix. Key characteristics of the survey respondents are presented in Table 1. The values in Table 1 show that the average age of the survey respondents at the time of the survey (2017) was 59.5 years, while the average age of primary operators in the state was 56.2 years as per the 2017 Census (USDA 2019). As per the 2017 USDA Census, the average farm size in South Dakota was 584 hectares, much smaller than the study sample's average of 771 hectares.

Table 1 The key characteristics of survey respondents

Characteristic	Count	Mean
Age (years)	195	59.5
College education (%)	197	45.6
Cropland (hectares)	198	771.1
Proportion raising cattle (%)	198	51.5
Proportion with off-farm employment (%)	187	22.5

Source Authors' survey in 2017. Note: Count refers to the number of observations used to calculate the mean values. Those who attended some college (including community college) are also included in the college education category

Empirical model

Adoption of PATs

The expected random utility framework was used to model a producer's adoption decision. Suppose there are N producers in a region and consider that producer i will adopt a PAT if the expected utility of adoption (which includes stochastic monetary profit) exceeds the utility of non-adoption. Further, let $Y_i = 1$ denote the decision of producer i to adopt a PAT and $Y_i = 0$ denote the decision to not adopt the PAT. Let the perceived profit associated with the adoption decision be denoted by $\pi_i^{Y_i}$. Adoption occurs when

$$E(U(1, \pi_i^1, X)) > E(U(0, \pi_i^0, X)), \quad (1)$$

where X represents the matrix of explanatory variables that includes farm and farmer characteristics.

The producer's utility function $U(Y_i, \pi_i^{Y_i}; X)$ is unknown to us, and the deterministic part of the utility function is $V(Y_i, \pi_i^{Y_i}; X)$, so the inequality in (1) can be written as

$$V(1, \pi_i^1, X) + U_1 > V(0, \pi_i^0, X) + U_0, \quad (2)$$

where U_1 and U_0 are independently and identically distributed random disturbances with zero means and unit variances.

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

$$Y_i^* = \beta' X_i + \epsilon_i, \quad (3)$$

where Y_i^* is the latent variable, and X_i is the set of observable farm and farmer characteristics.

Only the binary outcome Y_i (whether producer i has adopted the PAT or not) is observed, so Eq. (3) can be empirically estimated as Eq. (4) using a univariate probit model that uses maximum likelihood estimation (Tey and Brindal 2012):

$$Y_i = \beta' X_i + \epsilon_i, \quad (4)$$

where β are parameters to be estimated.

To see whether the determinants of adoption vary between embodied-knowledge and information-intensive PATs, the study employed probit models separately for embodied-knowledge and information-intensive PATs, and also by combining them.

Adoption intensity of PATs

This study uses count models to investigate the determinants of adoption intensity of PATs (Greene 2003). The use of count models that focus on the number of technologies adopted is advantageous when there is a large number of component technologies and their use intensities are the focus of research (Isgin et al. 2008; Boyer et al. 2018). Since this study focuses on PATs with several component technologies and the potential for bundling technologies together, the number of technologies adopted was used as a measure of adoption intensity. Due to the indivisible nature of many component technologies, understanding the

determinants of intensity in terms of the number of technologies used by producers will be of interest to manufacturers, agribusinesses, and policymakers.

The adoption intensity variable takes on a discrete count of PATs adopted by a producer. For the embodied-knowledge PATs (Count_Embodied), the count value will range from zero to three, and for information-intensive PATs (Count_InformationIntensive) the count value will range from zero to six. When embodied-knowledge and information-intensive PATs are combined (Count_PATs), the count value will range from zero to nine. This study differs from Isgin et al. (2008) who used zero-inflated negative binomial regression to identify the determinants of adoption intensity of PATs in Ohio in the United States, in that the count model analyses were done separately for embodied-knowledge and information-intensive PATs, as well as together as a pooled model.

The dependent variable in the count model analysis takes on a non-negative integer value whose average is small and is assumed to follow a Poisson distribution with equal mean and variance (Greene 2003). In the data, the conditional variance is larger than the conditional mean for the two count variables; Count_InformationIntensive and Count_PATs. This suggests the presence of over-dispersion (Greene 2003) in the count data (for Count_InformationIntensive and Count_PATs). The use of a negative binomial model is recommended to address the over-dispersion in data (STATA 2015). Negative binomial regression models the log of the expected count as a function of the independent variables. The likelihood ratio test of the over-dispersion parameter α in the negative binomial regression (which checks for whether α is significantly different from zero or not) will suggest whether the use of the negative binomial regression approach is appropriate or not. When α is zero (not statistically different from zero), the negative binomial distribution is equivalent to a Poisson distribution. A goodness-of-fit analysis after Poisson regression will indicate whether Poisson regression is a good choice or not. The study employed both negative binomial and Poisson regressions, with details provided in the results section below. The following empirical model was used to estimate adoption intensity;

$$\text{Adoption intensity}_i = \gamma'X_i + \varepsilon_i, \quad (5)$$

where γ are parameters to be estimated.

Equation (5) was estimated separately for embodied-knowledge and information-intensive PATs and by combining all nine PATs included in the study. STATA was used to estimate count models for adoption intensity.

Variable selection

The review of the literature on the adoption of PATs in the United States, Canada, Australia, and Europe informed the selection of explanatory variables for the analysis. Most of the available studies focus on the adoption of any one or two of the following information-intensive technologies; yield monitoring, variable-rate technology, and remote sensing systems, or PATs overall. Previous research identified socio-demographic factors (e.g. age, education, computer confidence), financial resources/economic factors (e.g. income, land size), agroecological factors (e.g. geography, soil quality), institutional factors (e.g. markets, policies), and producer perceptions (e.g. perceptions about profitability, environmental benefits) as the major determinants of PAT adoption in general (Pierpaoli et al. 2013; Tey and Brindal 2012; Mitchell et al. 2018; Paustian and Theuvsen 2017; Reichardt and Jürgens 2009; Robertson et al. 2012; Tamirat et al. 2018; Isgin et al. 2008; Lambert et al. 2015; Roberts et al. 2004). However, studies on the adoption determinants of popular

embodied-knowledge PATs such as GPS guidance systems are relatively limited (Tey and Brindal 2012).

The following are the variables included in this analysis and the hypothesis associated with each. While the variables included in the model are expected to influence adoption decisions, it is unclear whether the hypothesized relationship holds for both embodied-knowledge and information-intensive PATs—this is an aspect explored in this study.

Age: Available evidence on the effect of age on adoption is mixed. While some studies have shown a negative effect of age on PAT adoption due to the short planning horizon available for older farmers (Roberts et al. 2004; Larson et al. 2008; Walton et al. 2008; D’Antoni et al. 2012), other studies have shown either positive effects (Isgin et al. 2008; Torbett et al. 2007) or no effect (Robertson et al. 2012). Given that the evidence on the effect of age is mixed, the hypothesis is tested that age has either a negative or no effect on PAT adoption and adoption intensity. Operator age is recorded as a continuous variable (number of years) in this study.

Education: Education is expected to improve a producer’s innovative capabilities through the acquisition of technological and entrepreneurial skills. Some studies show a positive relationship between education attainment and adoption of PATs (Walton et al. 2008; Larson et al. 2008; Tey and Brindal 2012; Pierpaoli et al. 2013). Other studies show education as not significant in PAT adoption decisions (Sevier and Lee 2004; Banerjee et al. 2008). Given the mixed evidence, the hypothesis is tested that education has either a positive or no effect on the adoption and adoption intensity of PATs. Education is included as a binary variable that takes the value of one if the operator has some college education or more and zero, otherwise.

Cropland: Economies of scale may play an important role in the ability of farmers to acquire capital-intensive technologies such as PATs. Some studies show a positive relationship between farm size and PAT adoption (Robertson et al. 2012; Walton et al. 2008; Pierpaoli et al. 2013). The hypothesis is tested that there is a positive relationship between cropland area and adoption and adoption intensity of PATs.

Operator off-farm income: Off-farm income acts as a source of external capital/financial resources, which are critical in the adoption of capital-intensive PATs (Tey and Brindal 2012). Alternatively, producers with off-farm income sources may choose to invest in acquiring land—a long-term investment option—or other assets, instead of investing in capital-intensive PATs. Furthermore, time constraints created by off-farm employment can have a positive or negative effect on the adoption of PATs. Therefore, the effect of operators’ off-farm income on adoption and adoption intensity of PATs is uncertain. To test the effect of operator off-farm income on adoption and adoption intensity, operator off-farm income was included as a binary variable that takes the value of one if the operator has off-farm income, and zero otherwise.

Land productivity: Soil quality, as a natural endowment, is important in agricultural technology adoption decisions (Tey and Brindal 2012; Pierpaoli et al. 2013). South Dakota topography and soil quality vary throughout the state. To capture the difference in cropland quality, a land productivity variable was created. To create this variable, data were collected from NASS on non-irrigated cropland cash rent (paid per acre) on South Dakota Farms in 2016 (NASS 2017). A threshold of \$420/hectare (\$170 per acre) county average was set,

with any county at or above this point being considered as having “highly productive land”. Land productivity is included as a binary variable that takes the value of one if cash rent per hectare is \$420 or more in the county where the farm is located and zero otherwise. The effect of land productivity on adoption and adoption intensity could be positive or negative. For example, a farm with highly productive land may need less hectares to be a viable farm, therefore having less hectares to spread the capital investment cost across, and thus resulting in a negative effect on adoption and adoption intensity. Conversely, a farm with low productivity may farm more hectares, therefore have more of a reason to adopt PATs because the cost is relatively less per acre. Because the effect of land productivity on the adoption and adoption intensity of PATs is uncertain, this study is used to test the effect.

Use of computer technology for farm accounting: Given that computer technology is an integral part of PATs, use of a computer/farmer’s confidence with the computer has been found to have a positive effect on the adoption of PATs (Isgin et al. 2008; Tey and Brindal 2012; Pierpaoli et al. 2013). The use of technology for farm accounting was included as a binary variable that takes the value of one if the operator uses a computer for accounting purposes, and zero otherwise. The hypothesis is tested that there is a positive relationship between computer use for farm accounting purposes and PAT adoption and adoption intensity.

Producer’s perception on profitability: Producers’ perception of profitability is attributed as one of the motivating factors in the adoption of PATs (Adrian et al. 2005; Tey and Brindal 2012; Pierpaoli et al. 2013). Profitability from the adoption of PATs can come from various paths including increases in input usage efficiency and productivity. In this study, information was gathered on producers’ perceptions of profitability/economic benefits from the adoption of PATs on a four-point Likert scale. A profitability index variable was created by taking the sum of the respondents’ scores associated with profitability aspects divided by the maximum potential score possible. Thus, the profitability index variable’s values range from zero to one. The hypothesis is tested that the profitability index has a positive effect on the adoption and adoption intensity of PATs.

Producer’s perception of environmental benefits: As noted earlier, PAT adoption has on-farm and off-farm environmental benefits. However, studies examining the relationship between producers’ perceptions of these environmental benefits and adoption decisions are limited. This study considers the effect of producers’ perceptions about the environmental benefits of PATs in their adoption and adoption intensity by including an environmental index variable. The hypothesis is tested that the environmental index has a positive effect on the adoption and adoption intensity of PATs.

A correlation matrix was used to check for the presence of multicollinearity among the explanatory variables. The correlation between the profitability index variable and environmental benefit index variable was 0.85. To test for the robustness of the results, regression models were estimated with only one of these variables at a time, as well as with both variables simultaneously. Akaike’s information criterion (AIC) and Bayesian information criterion (BIC) were used for each of the estimation models for comparison purposes.

Results and discussion

Adoption of precision agriculture practices in South Dakota

It is clear from Table 2 that GPS guidance, autosteer, yield monitor, and automatic section control systems are the most popular PATs, each with adoption rates of over 50% among the survey respondents. As reported by Miller et al. (2019), embodied-knowledge PATs such as GPS guidance, autosteer, and automatic section control are more popular than information-intensive PATs in South Dakota. Among the information-intensive PATs only yield monitor, which is considered as a benchmark information-intensive PAT (Miller et al. 2019), had an adoption rate exceeding 50%. Among the nine PATs the study covered, the following information-intense technologies are least popular: aerial satellite imagery, crop tissue sampling, and grid soil sampling. Table 2 further shows that overall PAT adoption rates among the South Dakota respondents exceeded 50%, driven mostly by large-scale adoption of embodied-knowledge PATs. It is evident from Table 2 that adoption rates varied greatly between PATs and adoption rates of embodied-knowledge PATs—which are easy to use and mostly available as part of machine upgrade purchases—are higher (72%) than those of information intense technologies (66%), which need additional skills and or resources for the efficient use of data generated for farm management purposes.

Table 3 shows the intensity of PAT adoption (number of PATs adopted) by survey respondents. Given that adoption rates of embodied-knowledge PATs are higher than information-intensive PATs in Table 2, and cumulative adoption rates of four or more PATs are high, the results in Tables 2 and 3 support previous findings that PATs are adopted in bundles of various combinations by producers (Schimmelpfennig 2016; Schimmelpfennig and Ebel 2016; Lambert et al. 2015; Miller et al. 2019).

Summary statistics of variables included in the regression models are presented in Table 4. Because of the higher adoption levels of embodied-knowledge PATs, the %age of adopters of any one of the PATs is high, at 86.6%. Table 4 indicates that among the survey respondents, relative to non-adopters, PAT adopters have larger amounts of cropland hectares, perceive the profitability and environmental benefits from PAT adoption to be higher, and are users of computer technology in farm accounting.

Table 2 PAT adoption rates among South Dakota respondents, 2017

Types of PATs	Adoption rate (%)
Embodied-knowledge	
Autosteer	73.7
GPS guidance system	75.8
Automatic section control/shut-offs	55.1
Information-intensive	
Yield monitor	68.7
Variable-rate system	50.0
Prescription field maps	50.5
Grid soil sampling	44.2
Crop tissue sampling	37.6
Aerial/satellite imagery	30.8

Table 3 Adoption intensity of PATs in South Dakota, 2017

Number of PATs	Frequency	Percentage
Zero	27	13.6
One	10	5.1
Two	17	8.6
Three	10	5.1
Four	22	11.1
Five	18	9.1
Six	18	9.1
Seven	26	13.1
Eight	30	15.2
Nine	20	10.1
N	198	100

Source Authors' survey

Table 4 Summary statistics of variables included in the regression models

Variable	Non-adopters	Adopters ^a	Whole sample
Age	60.0 (8.6)	58.5 (12.1)	58.7 (11.9)
Education level (some college education or not)	0.6 (0.5)	0.4 (0.5)	0.4 (0.5)
Cropland ('000 hectares)	0.2 (0.1)	0.9*** (1.0)	0.8 (1.0)
Land productivity (0/1)	0.4 (0.5)	0.3 (0.5)	0.3 (0.5)
Operator off-farm income (0/1)	0.4 (0.5)	0.2* (0.4)	0.2 (0.4)
Profit index (0–1)	0.0 (0.2)	0.8*** (0.3)	0.7 (0.4)
Environmental benefit index (0–1)	0.0 (0.2)	0.7*** (0.3)	0.6 (0.4)
Use of technology for farm accounting (0/1)	0.4 (0.5)	0.7*** (0.5)	0.7 (0.5)

^aIf a survey respondent adopted any one of the nine PATs included in the study, he/she is considered an adopter. Figures in parentheses are standard deviations

***, **, and * indicate as per t-test results mean values of variables are statistically different between adopters and non-adopters at 1%, 5%, and 10% significance levels, respectively

Determinants of PAT adoption

The results of the probit model on embodied-knowledge PATs and information-intensive PATs are presented in Tables 5 and 6, and the results from the pooled model are presented in Table 9 in the Appendix. Three separate models are estimated to address the multicollinearity between the profitability index variable and environmental benefit index variable. Model 1 includes the profitability index, but not the environmental benefit index. Model 2 includes the environmental benefit index, but not the profitability index. Model 3 includes both profitability and environmental benefit indices. The models' statistically significant goodness-of-fit measures are indicated by the Wald Chi-square values reported in the Tables.

The positive and statistically significant coefficient of cropland area in all three models in Tables 5, 6, and 9 support the hypothesis that farm size has a positive effect on the adoption of both embodied-knowledge and information-intensive PATs (Roberts et al. 2004; Lambert et al. 2015; Paustian and Theuvsen 2017; Tamirat et al. 2018). Also, the positive

Table 5 Results from the probit model on the adoption of embodied-knowledge PATs

Variables	Model 1	Model 2	Model 3
Age	0.02 (0.01)	0.02 (0.01)	0.01 (0.01)
Education level (college vs. not)	0.10 (0.36)	0.01 (0.33)	−0.04 (0.40)
Cropland (‘000 hectares)	2.88 (0.6)***	2.92 (0.63)***	3.45 (0.84)***
Land productivity (0/1)	0.60 (0.33)*	0.56 (0.33)*	0.69 (0.39)*
Operator off-farm income (0/1)	−0.04 (0.35)	−0.11 (0.33)	−0.08 (0.38)
Profit index (0–1)	1.60 (0.40)***	NA	6.92 (1.62)***
Environmental benefit index (0–1)	NA	0.99 (0.39)**	−5.42 (1.45)***
Farm accounting tech use (0/1)	0.36 (0.34)	0.46 (0.32)	0.34 (0.36)
Constant	−2.68 (0.99)***	−2.23 (0.94)**	−2.29 (0.94)**
Pseudo R ²	0.42	0.35	0.49
Wald chi ²	44.19	40.36	38.33
Correctly classified (%)	91.6	88.6	92.2
AIC	93.43	103.23	86.61
BIC	118.32	128.13	114.62
N	166	166	166

Models vary based on the inclusion/exclusion status of the profitability index and the environmental index variables

***, **, and * indicate coefficients are significant at 1%, 5%, and 10% significance levels, respectively. Figures in parentheses are robust standard errors

Table 6 Results from the probit model on the adoption of information-intensive PATs

Variables	Model 1	Model 2	Model 3
Age	0.01 (0.02)	0.01 (0.02)	0.01 (0.02)
Education level (college vs. not)	−0.17 (0.33)	−0.16 (0.31)	−0.15 (0.31)
Cropland (‘000 hectares)	1.28 (0.53)**	1.40 (0.55)**	1.27 (0.51)**
Land productivity (0/1)	0.79 (0.38)**	0.77 (0.37)**	0.80 (0.39)**
Operator off-farm income (0/1)	−0.94 (0.43)**	−1.01 (0.42)**	−0.96 (0.44)**
Profit index (0–1)	2.49 (0.55)***	NA	2.19 (0.98)**
Environmental benefit index (0–1)	NA	2.27 (0.61)***	0.34 (1.06)
Farm accounting tech use (0/1)	1.12 (0.39)***	1.19 (0.37)***	1.12 (0.39)***
Constant	−2.35 (1.27)*	−1.90 (1.41)	−2.34 (1.28)*
Pseudo R ²	0.57	0.53	0.57
Wald chi ²	27.87	22.22	32.13
Correctly classified (%)	93.3	94.6	93.9
AIC	75.99	82.39	77.88
BIC	100.84	107.23	105.83
N	165	165	165

Models vary based on the inclusion status of the profitability index and the environmental index variables

***, **, and * indicate coefficients are significant at 1%, 5%, and 10% significance levels, respectively. Figures in parentheses are robust standard errors

and statistically significant coefficient of the profitability index variable in Tables 5, 6 and 9 support the hypothesis that producers who perceive profitability to increase when using PATs are relatively more likely to adopt them (Barnes et al. 2019) and the effect is similar for embodied-knowledge and information-intensive PATs and when these two types of technologies are combined. A positive and statistically significant coefficient on the use of computer technology for farm accounting in Table 6 supports the hypothesis that producers with familiarity or confidence in using computers are more likely to adopt information-intensive PATs than those who do not use computers (Isgin et al. 2008; Pierpaoli et al. 2013). However, the statistical non-significance of the use of computer technology for farm accounting for embodied-knowledge PATs in Table 5 suggests that familiarity with computers is not a determinant in the adoption of embodied-knowledge PATs. The difference in the statistical significance of the coefficient on familiarity with computer use between Tables 5 and 6 also suggests the importance of examining the adoption of embodied-knowledge and information-intensive PATs separately. While the environmental benefit index variable is positive and statistically significant in Model 2 for Tables 5, 6 and 9, it is negative and statistically significant in Model 3 in Tables 5 and 9, and not statistically significant in Model 3 in Table 6. The difference in the statistical significance of the coefficient of the environmental benefit index variable between Models 2 and 3 may be because Model 2 captures the effect of a missing variable—the profitability index—and in Model 3, which includes the profitability index, the effect becomes negative due to the collinearity issues discussed earlier. However, the difference in the statistical significance of the environmental benefit index between embodied-knowledge PATs and information-intensive PATs is an aspect that needs investigation in future research. The positive and statistically significant coefficient on land productivity in embodied-knowledge and information-intensive PATs support the hypothesis that producers with high-quality land are more likely to adopt capital-intensive technologies such as PATs than those with low-quality land. Note that the statistical significance of the effect is higher (5%) for the adoption of information-intensive PATs relative to embodied-knowledge PATs (10%). As per the results in Table 5, the coefficient of the binary off-farm income variable is not statistically significant, which suggests that it is not an important determinant in the adoption of embodied-knowledge PATs. However, its negative and statically significant coefficient in Table 6 suggests that producers with off-farm income are less likely to adopt information-intensive PATs than those without.

Similar to Robertson et al. (2012), the results suggest that age is not significant in the producers' adoption decisions of embodied-knowledge and information-intensive technologies. Similar to Banerjee et al. (2008), Sevier and Lee (2004), and Tamirat et al. (2018), having a college education is not found to be an important determinant in PAT adoption. This may be because the availability of professional certification courses and/or availability of professional consultants outweigh the effect of college education on adoption decisions. However, lack of available data made it impossible to test this.

The information criteria and classification rate presented in Tables 5, 6 and 9 allows for a comparison between models. The overall results in Tables 5, 6 and 9 suggest that although more or less similar, there are some differences in the determinants of adoption of embodied-knowledge and information-intensive PATs, which highlight the importance of examining these adoption decisions as two separate decisions.

Determinants of adoption intensity of PATs

As mentioned previously, due to the presence of overdispersion in the data, a negative binomial regression was initially selected to identify the determinants of adoption intensity (Isgin et al. 2008; STATA 2015). However, the likelihood ratio test of over-dispersion parameter α from the negative binomial regression could not reject the hypothesis that α is equal to zero. Hence, instead of negative binomial regression, Poisson regression was used and goodness of fit analysis was conducted to verify the appropriateness of the Poisson regression model. Similar to the probit models discussed above, all three models (Models 1, 2, and 3) were used for the Poisson regressions. Results from the Poisson regression model are presented in Tables 7, 8, and 10

Similar to the adoption models, the cropland size variable has a positive and statistically significant effect on the adoption intensity of embodied-knowledge and information-intensive PATs (Tables 7, 8, 10). The coefficient value of cropland size in the model in Table 7 suggests that a one-unit increase in cropland hectares is associated with an increase of 0.11 in the difference in the logs of expected counts in Model 1, while holding the other variables in the model constant. Unlike in the models of PAT adoption, familiarity with computers has a positive and statistically significant effect on the adoption intensity of embodied-knowledge and information-intensive PATs. While the land productivity variable has no statistically significant effect on the adoption intensity of embodied-knowledge PATs (Table 7), the effect is positive and statistically significant for information-intensive PATs in Models 1 and 3 in Table 8. The positive and statistically significant effect of land productivity on the adoption intensity of information-intensive PATs suggests that adoption intensity is higher among producers with high-quality land than among those with low-quality land. Similar to the adoption models, the profitability index has a positive and statistically significant effect on adoption intensity of embodied-knowledge as well as and

Table 7 Results from the Poisson regression model on the adoption intensity of embodied-knowledge PATs

Variables	Model 1	Model 2	Model 3
Age	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
Education level (college vs. not)	−0.02 (0.07)	−0.03 (0.07)	−0.02 (0.07)
Cropland ('000 hectares)	0.11 (0.03)***	0.14 (0.02)***	0.12 (0.03)***
Land productivity (0/1)	0.03 (0.07)	0.00 (0.08)	0.03 (0.08)
Operator off-farm income (0/1)	−0.13 (0.09)	−0.13 (0.10)	−0.13 (0.09)
Profit index (0–1)	1.01 (1.17)***	NA	0.90 (0.20)***
Environmental benefit index (0–1)	NA	0.70 (0.12)***	0.13 (0.13)
Farm accounting tech use (0/1)	0.16 (0.09)*	0.20 (0.09)**	0.16 (0.09)*
Constant	−0.37 (0.25)	−0.04 (0.24)	−0.37 (0.25)
Pseudo R ²	0.08	0.07	0.08
Wald chi ²	71.20	70.85	72.95
AIC	507.65	516.32	509.37
BIC	532.55	541.22	537.38
N	166	166	166

Models vary based on the inclusion status of the profitability index and environmental index variables

***, **, and * indicate coefficients are significant at 1%, 5%, and 10% significance levels, respectively. Figures in parentheses are robust standard errors

Table 8 Results from the Poisson regression model on the adoption intensity of information-intensive PATs

Variables	Model 1	Model 2	Model 3
Age	−0.00 (0.00)	−0.00 (0.00)	−0.00 (0.00)
Education level (college vs. not)	0.01 (0.09)	−0.00 (0.09)	0.01 (0.09)
Cropland ('000 hectares)	0.09 (0.03)***	0.16 (0.04)***	0.11 (0.03)***
Land productivity (0/1)	0.19 (0.08)**	0.13 (0.09)	0.17 (0.08)**
Operator off-farm income (0/1)	−0.22 (0.12)*	−0.21 (0.13)	−0.21 (0.11)*
Profit index (0–1)	1.82 (0.21)***	NA	1.37 (0.29)***
Environmental benefit index (0–1)	NA	1.34 (0.17)***	0.52 (0.22)**
Farm accounting tech use (0/1)	0.24 (0.13)*	0.28 (0.13)**	0.23 (0.13)**
Constant	−0.64 (0.32)**	−0.09 (0.31)	−0.64 (0.32)**
Pseudo R ²	0.21	0.18	0.21
Wald chi ²	121.67	108.88	125.91
AIC	624.78	641.51	620.73
BIC	650.10	666.83	649.21
N	175	175	175

Models vary based on the inclusion status of the profitability index variable and environmental index variable

***, **, and * indicate coefficients are significant at 1%, 5%, and 10% significance levels, respectively. Figures in parentheses are robust standard errors

information-intensive PATs. However, there is a difference in the direction and statistical significance of the coefficient on the environmental benefit index variable between the adoption models in Tables 5 and 6 and adoption intensity models in Tables 7 and 8. As per the results in Table 8, producers with higher positive perceptions have a positive and statistically significant effect on the adoption intensity of information-intensive PATs than their counterparts, while the effect is inconclusive for the embodied-knowledge PATs. Similar to the adoption decision results, operator off-farm income has no statistically significant effect on adoption intensity of embodied-knowledge PATs and has a negative and statistically significant (albeit at 10%) effect on adoption intensity of information-intensive PATs. Similar to the adoption models, the study finds no evidence of a statistically significant effect for age and education in the adoption intensity of PATs.

Overall, findings from the study show that the effect of cropland size, producers' perceptions of profitability, and operator off-farm income are similar for both adoption and adoption intensity of embodied-knowledge and information-intensive PATs. However, there are differences in statistical significance of the effect of land productivity and familiarity with computer use between adoption and adoption intensity and between embodied-knowledge and information-intensive PATs. The effect of producers' perception of the environmental benefits of PATs is inconclusive and needs to be investigated in future research.

Conclusion and implications

This study analyzes the determinants of adoption and adoption intensity of embodied-knowledge and information-intensive PATs, separately and by pooling them together. The study uses survey data of agricultural producers in eastern South Dakota. A probit model

was used for examining the determinants of adoption of PATs and Poisson regression was used to analyze adoption intensity.

The study shows that adoption rates of embodied-knowledge PATs are higher than those of information-intensive PATs. Cropland size, producer perceptions of PAT profitability, and land productivity each has a positive effect on the likelihood of adoption of embodied-knowledge PATs. In addition to these factors, prior use of computers has a positive effect, and operators with off-farm income have a negative effect on the likelihood of adoption of information-intensive PATs. The effects of perceived environmental benefits of PATs on the likelihood of adoption of embodied-knowledge PATs and information-intensive PATs remain inconclusive. Cropland size, prior use of computers in farm accounting, and producers' perception of profitability have positive effects on the adoption intensity of both embodied-knowledge and information-intensive PATs. Also, land productivity and having a perception of environmental benefits have positive effects, and operators with off-farm income has a negative effect on the adoption intensity of information-intensive PATs.

The results from the study suggest that there are some differences in determinants between adoption and adoption intensity of embodied-knowledge PATs and information-intensive PATs, and the analysis that pools technologies together masks differences between the determinants of embodied-knowledge and those of information-intensive PATs. Given that the adoption and adoption intensity of information-intensive PATs are lower than the embodied-knowledge PATs, the improved understanding of the determinants of adoption and adoption intensity of information intensive PATs put forth by this study may serve to help guide policies and programs. Findings from the study imply that improved communication emphasizing the environmental benefits would be beneficial—not only from a public policy point of view, but could be part of marketing programs and outreach efforts in efforts to scale up the PAT adoption. Findings from the study suggest that extension and outreach efforts on PATs should target farmers with large farm sizes and those having access to high-quality land. Additionally, extension efforts focusing on familiarizing farmers with using computers and applications for farm management have the potential to increase the likelihood of adoption of information-intensive PATs. Overall, this study provides insights on developing programs, policies, and outreach efforts that encourage the adoption and adoption intensity of both embodied-knowledge and information-intensive PATs.

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Appendix

Description of PATs used in the study

Autosteer

Autosteer has been in use since the mid-1990s to drive tractors to improve performance and operation precision. The use of autosteer allows producers to reduce compaction on their fields, reduce fuel usage and fuel cost, and save operating time (McBratney et al. 2005; D'Antoni et al. 2012).

GPS-guidance systems

GPS-guidance systems are similar to autosteer, except more advanced than autosteer from earlier days. GPS-guidance system is also aimed at improving performance and operation precision. This study includes autosteer and GPS guidance systems, as two separate technologies to avoid any confusion among producers regarding the use of terms based on their familiarity and PAT usage. There might be some producers who have some machines with auto-steer and some with GPS-guidance systems.

Automatic section controls/shut-offs

These are PATs that enable the applicator to track data from an area covered by a planter/fertilizer and shut off those individual units to avoid over-application of inputs. Automatic section controls/shut-offs enable producers to improve input-use efficiency.

Yield monitor

Early versions of yield monitors were used mainly for tracking yields and exploratory data analysis on yields for marketing purposes. Technology advancements enable it to leverage the spatial variability for input management (e.g. fertilizer and seeding rates) by integrating field-level yield data with data from other component technologies such as field maps, grid soil sample data, etc. (Stafford et al. 1996; Lowenberg-DeBoer and Erickson 2019).

Variable-rate systems

Variable-rate systems encompass variable rate technologies used for fertilizer application, seeding, etc. VRTs leverage spatial variability for efficient input management and thus have the potential to increase profitability and reduce the negative environmental effects of intensive agricultural production practices (Roberts et al. 2004; Robertson et al. 2012; Lawes and Robertson 2011).

Prescription field maps

Site-specific precision field map tell the controller how much input (fertilizer, seed, etc.) to apply based on the location of the equipment in the field. Prescription field maps connect geographic information to soil test results and support producer decision making.

Grid soil sampling

Grid soil sampling reveals how nutrients are distributed across a field and thus help in the efficient management of fertilizer types, quantity, and fertilizer costs. It prevents over-application of fertilizer in areas where nutrient levels are high and allows for soil enrichment in areas where nutrient levels are low.

Crop tissue sampling

Crop tissue testing is useful in diagnosing nutrient deficiencies in field crops. The use of crop tissue testing as a reliable diagnostic tool requires correlating nutrient concentrations with crop yield response.

Table 9 Results from the probit model on the adoption of PATs (pooled model)

Variables	Model 1	Model 2	Model 3
Age	0.02 (0.02)	0.03 (0.02)	0.02 (.02)
Education level (college vs. not)	−0.31 (0.57)	−0.27 (0.50)	−0.37 (0.57)
Cropland (*000 hectares)	3.01 (1.26)**	2.66 (0.89)***	3.05 (1.29)**
Land productivity (0/1)	1.04 (0.55)**	1.00 (0.50)**	1.02 (0.56)*
Operator off-farm income (0/1)	−0.54 (0.59)	−0.75 (0.57)	−0.53 (0.60)
Profit index (0–1)	3.10 (0.67)***	NA	6.72 (2.07)***
Environmental benefit index (0–1)	NA	3.24 (0.88)***	−3.73 (1.73)**
Farm accounting tech use (0/1)	1.05 (0.54)**	1.20 (0.52)**	0.98 (0.52)*
Constant	−2.70 (1.48)*	−2.59 (1.57)*	−2.45 (1.47)*
Pseudo R ²	0.65	0.59	0.65
Wald chi ²	28.17	29.66	29.12
Correctly classified (%)	94.5	94.6	95.8
AIC	48.38	53.04	49.77739
BIC	73.28	77.93	77.78528
N	166	166	166

Models vary based on the inclusion status of the profitability index variable and the environmental index variable

***, **, and * indicate coefficients are significant at 1%, 5%, and 10% significance levels, respectively. Figures in parentheses are robust standard errors

Table 10 Results from the Poisson model on adoption intensity of PATs (pooled model)

Variables	Model 1	Model 2	Model 3
Age	0.00 (0.00)	−0.00 (0.00)	0.00 (0.00)
Education level (college vs. not)	0.00 (0.07)	−0.00 (0.07)	0.00 (0.06)
Cropland (‘000 hectares)	0.10 (0.02)***	0.14 (.02)***	0.11 (0.02)***
Land productivity (0/1)	0.13 (0.07)*	0.08 (0.07)	0.11 (0.07)*
Operator off-farm income (0/1)	−0.18 (0.09)**	−0.17 (0.10)*	−0.18 (0.09)**
Profit index (0–1)	1.33 (0.16)***	NA	1.03 (0.21)***
Environmental benefit index (0–1)	NA	0.97 (0.13)***	0.35 (0.15)**
Farm accounting tech use (0/1)	0.22 (0.09)**	0.25 (0.10)**	0.21 (0.09)**
Constant	0.27 (0.24)	0.66 (0.24)***	0.27 (0.24)
Pseudo R ²	0.18	0.16	0.19
Wald chi ²	118.52	100.88	125.76
AIC	718.27	737.92	715.48
BIC	743.17	762.82	743.49
N	166	166	166

Models vary based on the inclusion status of the profitability index variable and the environmental index variable

***, **, and * indicate coefficients are significant at 1%, 5%, and 10% significance levels, respectively. Figures in parentheses are robust standard errors

Aerial/satellite imagery

Aerial/satellite imagery is used to create zone maps using sensors in the sky. Until recently, usefulness of satellite remote sensing to producers was limited by long re-visit times, cloud cover, cost, poor spatial resolution, and the lack of techniques to process imagery for agricultural applications. However, with the growing number of satellites and the increase in imagery resolution, the use of satellite imagery for variable rate input application is increasingly feasible.

See Tables 9 and 10.

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