



Examining the social and biophysical determinants of U.S. Midwestern corn farmers' adoption of precision agriculture

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Abstract

Precision agricultural technologies (PA) such as global positioning system tools have been commercially available since the early 1990s and they are widely thought to have environmental and economic benefit; however, adoption studies show uneven adoption among farmers in the U.S. and Europe. This study aims to tackle a lingering puzzle regarding why some farmers adopt precision agriculture as an approach to food production and why others do not. The specific objective of this study is to examine the social and biophysical determinants of farmers' adoption of PA. This paper fills a research gap by including measurements of farmer identity—specifically their own conceptions of their role in the food system—as well as their perceptions of biophysical risks as these relate to the adoption of PA among a large sample of Midwestern U.S. farmers. The study has identified that farmer identity and perceptions of environmental risk do indeed influence PA adoption and that these considerations ought to be incorporated into further studies of PA adoption in other jurisdictions. The findings also appear to highlight the social force of policy and industry efforts to frame PA as not only good for productivity and efficiency but also as an ecologically beneficial technology.

Keywords Precision agriculture · Adoption · Farmer identity · Biophysical risks · Risk perception

Introduction

The adoption of precision agriculture (PA) has been well studied, a research agenda driven by a) policy commitments encouraging the widespread adoption of PA for sectoral and environmental sustainability (e.g. Khanna et al. 1999; Lambert et al. 2014), and b) the

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impossibility of making good on these commitments given uneven adoption of PA (Aubert et al. 2012; Bramley 2009; Reichardt and Jürgens 2009; Fountas et al. 2005; Batte and Arnholt 2003; Daberkow and McBride 2003; Stafford 2000). Rather than a specific technology, precision agriculture has been conceptualized as an “approach” to management which is driven by insights derived from large or big datasets which then allow for targeted agricultural decision-making (McBratney et al. 2005). Precision agriculture technologies include software and hardware for collecting big data—notably tractors with built in sensors—and also intelligent machines or algorithms for generating information from big datasets (Rossel and Bouma 2016; Driessen and Heutink 2015; Bongiovanni and Lowenberg-DeBoer 2004; Cox 2002). Some scholars and industry proponents describe PA as a “paradigm shift” (Rossel and Bouma 2016) in agricultural decision-making—one that ideally substitutes environmental information and knowledge for physical inputs, especially harmful ones like chemicals (Bongiovanni and Lowenberg-DeBoer 2004, see also Akhtman et al. 2017; Gebbers and Adamchuk 2010). According to Rossel and Bouma (2016), PA allows for “innovative approaches that characterize local soil and environmental conditions in space and time, improving the efficiency of production to maximize farm incomes and minimize environmental side effects” (Rossel and Bouma 2016). The term farming 4.0 has recently been used to characterize this new type of data-based agricultural practice (Clasen 2016).

Given its potential sustainability and economic gains, there has been considerable interest in farmer adoption of PA especially in relation to farm characteristics like size. Jensen et al. (2012) show that the intensity of a farming system influences the cost structure and resources available for the purchase of PA equipment. In general, several studies have found that large farm size is positively correlated with PA adoption (Lambert et al. 2014; Reichardt et al. 2009; Roberts et al. 2004; Daberkow and McBride 2003). In particular, owning more land has been shown to exert a greater positive influence on PA adoption and the literature has established that large commercial farms are more likely to benefit economically from the adoption of PA (Lambert et al. 2014; Jensen et al. 2012; Roberts et al. 2004). The high cost of many PA technologies is a known barrier to adoption among farmers (Reichardt and Jurgens Reichardt and Jürgens 2009), which disproportionately affects smaller, less intensive operations more vulnerable to financial risk. Not simply farm size, but also land characteristics such as soil quality have been studied in relation to PA adoption (Schoengold and Sunding 2014) where the benefits of PA have been witnessed as higher for soils with heterogeneity and permeability. Farm-level surveys have established a link between crops produced and PA adoption where cereals and specialty crops have shown to be positively associated with adoption (Walton et al. 2008).

As Paustian and Theuvsen (2017) put it in their study of PA adoption among a sample of German farmers, most research assumes the farmer as the main decision-maker in the adoption process or cycle (c.f. Mackrell et al. 2009); studies tend to focus on discrete socio-demographic variables such as age, tenure, and education in relation to adoption (Tey and Brindal 2012; Kutter et al. 2011; Robertson et al. 2011; Walton et al. 2010; Reichardt and Jürgens 2009; Daberkow and McBride 2003). Paustian and Theuvsen (2017) surveyed German farmers regarding their levels of PA adoption and found that farmers under 25 or over 55 were less likely to adopt. The link between farm tenure and adoption is “not unanimous and the subject has been widely debated” (Daberkow and McBride 2003). Although land ownership is likely to influence adoption especially when large capital investments related to PA are to be planned and implemented (Pierpaoli et al. 2013), land-renters or tenants may be interested to financially invest in PA technologies to gain better short-term returns to their investments (Daberkow and

McBride 2003). Roberts et al. (2004) found that PA adoption among US Southeastern cotton farmers depended on the level of a farmer's knowledge about the costs and benefits of PA, and other studies have confirmed a link between knowledge of and comfort with digital tools and PA adoption (Daberkow and McBride 2003). Some studies have considered the role of farmer relationships with influential actors in the wider PA innovation ecosystem (e.g. dealership experts) as they may impact adoption (see Busse et al. 2014), showing that the more cohesive these social networks the higher the rates of adoption.

This paper acknowledges the relative neglect—by previous studies—of the perspective of social actors themselves as it potentially impacts PA adoption (c.f. Mackrell et al. 2009). Beyond socio-demographic characteristics of the farmer, studies measuring a farmer's self-conceptions of how they fit into a social group—their social identity—as it relates to the use of PA are missing from the literature. This study therefore centralizes farmer identity as it relates to PA. The concept of identity is based on the symbolic interactionist theory developed by Stryker (1980) and refined by Burke (1991), where it can be understood as providing an answer to the question “who am I?” (Stenholm and Hytti 2014). That PA adoption studies have not focused on farmer identity is surprising given the literature on technology adoption at large which has established the central role of social processes such as identity in adoption and diffusion of farming practices and techniques (Burton and Wilson 2006). Previous studies have examined the role of farmer identity in relation to farmers' use of soil and water quality enhancement practices (McGuire et al. 2013; Blackstock et al. 2010; Burton and Wilson 2006), adoption of organic agricultural techniques (Sutherland et al. 2011), and development of new farm business enterprises (Stenholm and Hytti 2014). Studies have found that farmers are more likely to use certain technologies if these are located within their broader farming culture. In other words, farmers adopt practices or tools if they feel their use can provide them with a sense of meaning in relation to how they see themselves and their place among others with whom they identify.

Among existing studies of identity as it influences agricultural technology adoption, a key study revealed that “Conservationist” and “Civic-minded” identities can be more consequential than “Productivist” identity for conventional Midwestern U.S. farmers in their ability to meet societal and community-level expectations of eliminating the negative impacts of agriculture on water resources through changes in farming practices (McGuire et al. 2015). Still other work has highlighted similar self-conceptions are socially embedded processes and has demonstrated that farmers can hold competing identities until one becomes dominant or “activated” depending on a local situation (McGuire et al. 2013, 2015; Roesch-McNally et al. 2018). For example, a farmer who may want to use a practice such as cover crops in their farm management system but does not because a parent owns the land and forbids use of such practice. In this case, the individual's identity as a son is more salient than his farmer identity (McGuire et al. 2015). Del Marmol et al. (2018) describe the feedback between technology and identity formation, where a farmer's adoption of novel technologies can actually trigger a “cascade effect” with the possibility to “transform the entire social fabric,” including the social identities of farmers. The effects of PA on farmer identity has received some attention in the literature. For example, Higgins et al. (2017) show that mechanization in dairy farming has led to changes in the temporality of business cycles and a subsequent redefinition of milk production as “commodified economic activity” with corollary shifts in farmer self-conceptions regarding what constitutes a “good farmer” (Higgins et al. 2017; see also Carolan 2017). Notably, not only can a farmers' social identity be shaped by technology adoption but it can also contribute to social, institutional, and,

significantly, technological change (Roesch-McNally et al. 2018). While previous studies have attended to the role of PA in identity (re)formation, this study is unique in examining the role of farmer self-conception in PA adoption.

This paper also attends to the role of environmental risk perception in PA adoption. Researchers have shown that a farmer's decision to adopt a new technology or practice can depend upon their perceptions about their perception of the risk of biophysical changes to their farm operation (Gardezi and Arbuckle 2017, 2018). Risk perceptions are “a person's subjective judgment or assessment of risk. It is how risk and uncertainty are socially constructed and perceived” (Gardezi and Arbuckle 2018). Inclusion of such measures of risk perception is motivated by a social-ecological systems (SES) theoretical frame in which farming is seen as bringing together a dynamic feedback between nature, actors, technologies and organizations (Roesch-McNally et al. 2018; Freudenburg et al. 1995). Thus, changes in natural systems can modulate farmers' risk preferences and subsequently their decisions about adoption of new practices and technology. For example, farmers who observe erosion in their fields (Romig et al. 1995) and changes in seasonal precipitation (Morton et al. 2015) are more likely to use no-till and cover crop to reduce soil erosion on their farm. Few studies have examined the relationship between farmer's perceptions of biophysical risks and use of PA (c.f. Higgins et al. 2017), still it can be inferred that PA technologies may help farmers to actively manage environmental risks by allowing greater control of farming operations. This study attempts to understand the perceived attributes of risks and how they may affect adoption of PA among the sample group of U.S. Midwestern farmers.

The objective of this paper is to examine the social and biophysical determinants of farmers' use of PA technologies. Several hypotheses are examined (Fig. 1): Farm operators with higher levels of farm size (H1), farm sales (H2), education (H3), diversified cropping systems (H4), and concern about environmental risks, including risks of drought (H5), flood (H6), soil erosion (H7) and climate change (H8) will demonstrate higher propensity to adopt PA. Farmer's social identities (H9) and land tenure (H10) will be significantly related to adoption of PA, but direction of this relationship cannot be ascertained, at the outset. Watershed-level biophysical factors, including daily (H11) and seasonal precipitation (H12), drought (H13) and marginal soil (H14) will be positively associated with adoption of PA.

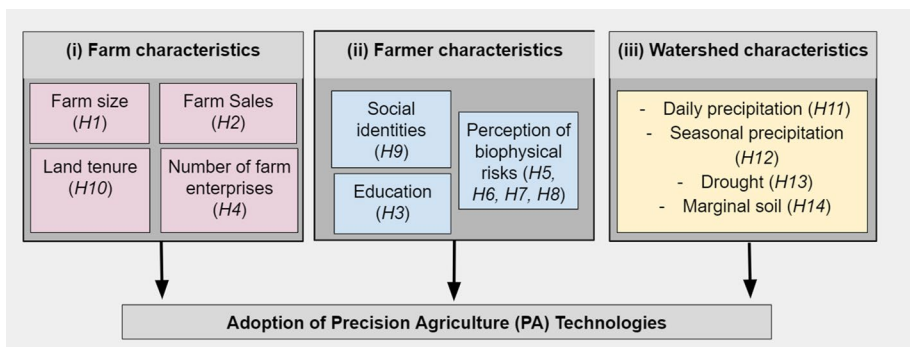


Fig. 1 Hypotheses for this paper's study of PA adoption (authors' own)

Methods

Study region

The study region comprises 22 hydrological watersheds (HUC6) in the Upper Midwestern United States (Fig. 2). This region is considered one of the most productive agricultural regions in the world for two crops: corn and soybean. In addition to providing economic benefits to the U.S. national economy, a third of the global corn supply comes from this region. The region has marked spatial and temporal variations in precipitation and temperature.

Data collection

Data collection was collected in two ways: (1) farmer surveys and (2) secondary data on farm-level and watershed-level sociodemographic and biophysical factors.

Farmer survey

Primary data for the study comes from a 2012 survey of corn and soybean farmers in the Midwestern U.S. The survey was designed and implemented by a large interdisciplinary team of social and natural scientists and included questions about farmers' use of various farming practices, techniques, and technologies, including precision agriculture. The sampling approach of this survey allows survey results to be generalized to large-scale farmers who produced the highest proportion of corn and soybean in this region. Hence, farmers whose revenue exceeded \$100,000 per year and farm size was larger



Fig. 2 Map of 22 hydrological watersheds associated with the study region

than 80 acres were included in the sampling frame. The survey was administered using a three-wave mailing process. It was mailed to 18,707 farmers that were stratified in 22 Hydrological Unit Code 6 (HUC6) watersheds (Fig. 2). This was followed by a reminder postcard, and a final survey sent to non-responders. Almost 5 000 farmers responded to the survey (26% response rate).

The HUC6 watersheds were selected as the higher-order unit for sampling for various reasons. First, farming systems are guided by environmental conditions, such as precipitation trends that can be homogenous within each watershed. Farmers' use of new farming practices, techniques, and technologies can be affected by changes in biophysical conditions. These environmental conditions can vary substantially across these 22 watersheds spanning a large geographical area. The HUC6 approach to sampling is useful for analysis in this paper, which aims to examine how biophysical conditions can influence farmers' use of precision agriculture technologies.

Secondary data

Secondary data used in the study allows for an examination of the potential influence of biophysical (e.g. drought, extreme precipitation) and economic (e.g. farm size, number of agricultural enterprises) characteristics to understand farmers' use of precision agriculture. Data are from four sources. Data on precipitation and temperature are from the National Weather Service (NWS) Cooperator Observer (COOP) archive. NWS-COOP is the most robust source of temperature and precipitation records that are observed daily over 11 000 locations across the U.S. Soil conditions for the watershed are from the Soil Survey Geographic (SSURGO) database. The SSURGO database provides comprehensive recent and distant past information about soil conditions at multiple spatial scales across the U.S. Drought data is from the U.S. Drought Monitor, which produces weekly maps showing areas that are in drought conditions (construction of the weather and soil variables are discussed in "[Environmental variables](#)" section). Lastly, farm/farmer socioeconomic details, such as farm size, number of farm enterprises (see "[Control variables](#)" section for details on measuring this variable) and farm sales are from the U.S. Agricultural Census, implemented every 5 years by United States Department of Agriculture's (USDA) National Agricultural Statistics Service to collect uniform producer-level data.

Measures

Outcome variable

Use of precision agriculture (*precision*) is measured through a single survey question that asked respondents whether they use 'Precision agriculture technology such as GPS, GIS, and variable-rate technology.' The respondents were asked to consider the farmland that they owned or rented and then choose from the following responses: 'practice used', 'familiar with, not used', and 'not familiar with'. The last two categories were combined and transformed as 'not used'. The outcome variable *precision* is binary (0 or 1) and 2680 (56%) respondents stated that they were currently using precision agriculture.

Predictor and control variables

Farmer identities Farmer identity is measured through 22 survey questions about what makes a ‘good farmer’. These questions were designed from literature (Burton and Wilson 2006) related to farmer identity and examined possible perceived qualities of a ‘good farmer’ (see Table 1). Respondents answered these questions on a 5-point scale ranging from 1 (strongly disagree) to 5 (strongly agree).

An exploratory factor analysis (EFA) was used to statistically condense information from these twenty-two identity questions into socially meaningful identity groups or types. Several cursory checks were used to ensure that the data was factorable. First, correlations between all twenty-two variables were moderately low. Second, the Kaiser–Meyer–Olkin measure of sampling adequacy was .91 (overall) and individual values were higher than .8. These two criteria suggest that the 22 variables were factorable. A scree plot was used to extract the appropriate number of factors. A scree plot is a line plot that shows the proportion of total variance explained by each factor component. According to the scree plot, beyond four factors, each successive factor accounted for even smaller proportions of the total variance. Thus, four factors were extracted. The oblique rotation method for EFA was used because the inter-factor correlation matrix depicted low correlation between four extracted factors (highest correlation was .29).

The exploratory factor analysis revealed four statistically robust and theoretically cogent factors. These factors (or identity types) were labelled Productivist, Conservationist, Expert and Listener (Table 1). Some survey questions about what constitutes a ‘good farmer’ that loaded highly on the Productivist identity were ‘highest yields per acre’ and ‘highest profit per acre’ (see Table 1). Some survey items relevant to the Conservationist identity were: ‘minimize nutrient runoff into waterways’ and ‘minimize pesticide use’. The Expert category included questions that depict farmers’ perceived importance in their social network. These questions are: ‘Other farmers tend to look at me for advice’ and ‘I consider myself to be a role model for other farmers’. The Listener identity illustrates farmers’ perceived appreciation of being an active learner and experimenter in their community. Survey questions that loaded highly on this identity included: ‘It is important for me to visit other farms to look at their practices’, among other questions shown in Table 1. While previous research has empirically developed two most commonly used identities: Productivist and Conservationist identities (Burton 2004; Burton and Wilson 2006), ‘Expert’ and ‘Listener’ do not appear in prior literature and these labels emerged from analyzing respondent’s perception of a good farmer. Finally, the factor scores associated with each farmer identity were normalized to create a range of relative scores from 0 to 1 (Table 2) see Gardezi and Arbuckle 2017).

Risk perceptions variables Four variables were included to measure risk perceptions or magnitude of concern that farmers have regarding longer periods of drought (*Drought concern*), increased flooding (*Flood concern*), soil erosion (*Erosion concern*), and climate change and variability (*Climate concern*). Concern about droughts, flooding, and erosion were measured on a four-point concern scale from *not concerned* (1) to *very concerned* (4). Concern for climate change was measured through a single item that asked respondents to rate their agreement with the statement, ‘My farm operation will likely be harmed by climate change’. This question measured respondents’ perception of the risk associated with climatic change and variability.

Table 1 Summary of farmer identity types, factor loadings, and communalities from exploratory factor analysis

Item	Factor loading	h^2	α
Productivist			.77
Most up-to-date equipment	.77	.61	
Crops planted first	.71	.51	
Highest yields per acre	.70	.53	
Maximize government payments	.64	.43	
Highest profit per acre	.64	.45	
Latest seed chemical technology	.58	.47	
Conservationist			.90
Think beyond their own farm to socio-ecological health	.80	.62	
Managed for profitability and environment	.79	.62	
Minimize nutrient runoff into waterways	.78	.61	
Minimize soil erosion	.77	.60	
Increase soil organic matter	.76	.59	
Health of streams	.74	.56	
Puts long-term conservation before short-term profits	.73	.54	
Scouts before spraying	.71	.51	
Minimize pesticide use	.62	.41	
Manages for reducing income volatility	.58	.40	
Expert			.81
Other farmers tend to look to me for advice	.86	.74	
I consider myself to be a role model for other farmers	.86	.76	
Crop advisors involved in agriculture tend to look at me for advice	.82	.67	
Listener			.55
It is important for me to visit other farms to look at their practices	.79	.63	
Willing to try new practices and approaches	.78	.61	
It is important for me to talk to other farmers about new practices	.49	.47	
Kaiser–Meyer–Olkin measure of sampling adequacy			.91
Bartlett's test of sphericity			$p < .01$
Eigenvalue			
Productivist		5.59	
Conservationist		3.02	
Expert		2.21	
Listener		1.52	
% of variance (cumulative)			56%

h^2 communality, α Cronbach alpha

Environmental variables Five variables were included to measure environmental variables at the level of the watershed. These included: extreme daily precipitation (*Daily*), seasonal precipitation (*Seasonal*), drought (*Drought*) and marginal soil (*Marginal*). Daily extreme precipitation (*Daily*) was measured by station-level precipitation data (1971–2011) that was obtained from the National Weather Service (NWS) Cooperative Observer (COOP) stations archive (Loy et al. 2013). Daily percentiles are month-specific; for example, daily

Table 2 Multilevel logistic regression of farmers' use of precision agriculture (PA) odds ratios (OR) with standard errors—Random intercepts

Level 1: farmers	
Constant	.74*** (1.04)
Farmer identities	
Productivist	1.09* (1.04)
× Owned	1.00 (1.11)
× Rented	.99 (1.17)
Conservationist	1.18*** (1.05)
× Owned	.93 (1.11)
× Rented	.68** (1.17)
Expert	1.36*** (1.05)
× Owned	.73*** (1.12)
× Rented	1.18 (1.18)
Listener	1.11** (1.05)
× owned	.90 (1.11)
× Rented	1.05 (1.17)
Risk perceptions:	
Drought concern	1.01 (1.04)
Flood concern	1.13*** (1.04)
Erosion concern	.92** (1.04)
Climate change concern	1.06 (1.04)
Demographic	
Tenure	
Land owned	.65*** (1.12)
Land rented	1.66*** (1.21)
Education	1.23*** (1.03)
Number of farm enterprises	.75*** (1.04)
× Owned	.97 (1.11)

Table 2 (continued)

Level 1: farmers	
× Rented	1.38** (1.18)
Farm sales (log)	1.42*** (1.09)
× Owned	.71*** (1.13)
× Rented	.87 (1.40)
Farm size (log)	1.58*** (1.08)
× Owned	.77* (1.16)
× Rented	1.27 (1.36)
Level 2: watershed	
Environmental factors	
Daily precipitation	1.10** (1.04)
Seasonal precipitation	1.23*** (1.05)
Drought	1.16*** (1.04)
Marginal soil	.82*** (1.05)
Model characteristics	
Observations	3 574
Log Likelihood	−2 085.48
Akaike Inf. Crit.	4 238.97
Pseudo-R ² (Tjur's D)	.18
Interclass correlation (ICC)	.05

Reference category for the variable 'Tenure' is 'owned and rented'

* $p < .1$; ** $p < .05$; *** $p < .01$

precipitation for May was constructed by aggregating all daily precipitation for May across all 41 years (1971–2011). Values at the 99th percentile (extreme values) from this distribution of daily precipitation were used to construct Daily extreme precipitation (*Daily*). Seasonal precipitation (Seasonal) was measured as the median rank of the total precipitation for April 1 through September 30 between 1971 and 2011, dates that coincide with the Upper Midwestern growing season. The rank was calculated as a relative measure (percentile) of each year's seasonal precipitation in comparison to the cumulative distribution of 41 years (Loy et al. 2013).

Drought (*Drought*) was measured using the U.S. Drought Monitor, which quantifies severity of drought in the U.S. over many locations each week. The drought monitor categories range from D0 (abnormally dry) to D4 (exceptional drought). To quantify long-term drought exposure, Loy et al. (2013) constructed a variable $d_{(i,t)}$, where $d = x$, if location i in week t was in drought condition x (where x could take values from D0 to D4). Watershed-level summaries

were obtained through the median of these drought values over 5 years before the survey was conducted (2007–2011) (Loy et al. 2013).

The classification of marginal versus non-marginal land (*Marginal*) was characterized by the USDA Natural Resource Conservation Service's (NRCS) land capability classification system (Loy et al. 2013). The capability system categorizes land according to the severity of land degradation, ranging from practicing caution when growing crops (class 4) to a restriction on commercial crop production (class 8). The percentage of marginal land in each watershed are county-specific and calculated from the Soil Survey Geographic (SSURGO) database. The percentage of marginal land was computed by summing the capability acreages for classes 4–8 for each county and creating a proportion of all acres in the county. These proportions were aggregated for each watershed in the study region.

Control variables Five variables were included in the model to measure farm and farmer specific background factors. They included land tenure or whether the respondent owned, rented, or owned and rented their farm land (*Tenure*). Other control variables were the highest level of education (*Education*); value of farm sales (*Farm sales*), size of farming operation (*Farm size*), and the number of agricultural enterprises (*Enterprises*). For the construction of the *Enterprise* variable, 2012 Agricultural Census data was used to calculate respondent's cropland area for nine enterprises, including corn, soybeans, wheat, oats, barley, rye, vegetables, fruits/nuts, and livestock (hogs and cows). Each enterprise was assigned '1', if at least 1% of cropland area was being utilized for the enterprise. The total number of enterprises for each respondent was added.

Analytical approach

Farm characteristics and farmers' responses to survey questions are nested within shared hydrological conditions prevailing at the watershed level. Thus, a generalized linear mixed-model (GLMM) was used to simultaneously analyze two levels of data: farm and farmer-level data (level 1) and biophysical conditions for each watershed (level 2). GLMM is a suitable choice of analytical approach because it facilitates examination of random effects when the dependent variable is binary and belongs to the exponential family of distributions (Bolker et al. 2009). This study constructed a single model to examine the relationship between farmers' use of precision agriculture and farmer identities, risk perception, environmental factors and farm/farmer demographics. GLMM presents an opportunity to test both random intercept and slope for each watershed. A random intercept only model would suggest that each watershed will have the same slope (or relationships between predictors and outcome) as the overall regression line. A random slope model allows the predictors to have a different effect on the outcome variable for each watershed. It was examined whether a random slopes model would be suitable for modeling survey and secondary data. Since little variance was explained by the watershed (see "Results" section for detailed explanation), it was decided to include random intercepts (for each watershed) but not random slopes in the final model.

The observed proportion of farmer i using precision agriculture in a watershed j is given by P_{ij} . A logit function ($\text{logit}(x) = \ln[x/(1-x)]$) as the link function is expressed in the model as (Gardezi and Arbuckle 2019):

$$\text{logit}(P_{ij}) = B_{0j} + B_1 X_{ij} \quad (1)$$

Equation (1) shows that the intercept is assumed to vary across watersheds and the coefficient for the slope is fixed. This variation in intercept is modeled by the watershed-level variable W_j as follows:

$$B_{0j} = \gamma_{00} + \gamma_{01}W_j + u_{0j} \quad (2)$$

$$B_{1j} = \gamma_{10} + u_{1j} \quad (3)$$

Equations (2) and (3) is substituted into 1 and rewritten as:

$$\log it(P_{ij}) = \gamma_{00} + \gamma_{10}X_{ij} + \gamma_{01}W_j + u_{0j} + u_{1j} + \gamma_{10}X_{ij} \quad (4)$$

A mixed-effects model (GLMM) assumes that both farm (level 1) and watershed-level (level 2) factors can explain farmers' use of precision agriculture. Before fitting the GLMM, all level 1 variables were centered-within-context (CWC) and standardized. CWC includes rescaling variables by subtracting the group (watershed) mean and reintroducing group means at level 2. The distributions seem normal and symmetric, except for *farm sales* and *farm size*, which had skewed distributions. These variables were logarithmically transformed.

The intra-class correlation coefficient (ICC) or ρ measures the proportion of variance explained by the higher-order unit, in this case the 22 watersheds. The ICC can be measured by various methods (Snijders and Bosker 1999). This study used a conventional formula:

$$\rho = \frac{\tau_{11}}{\tau_{11} + \sigma^2} \quad (5)$$

τ_{11} is the amount of variance attributed to watershed differences or variance between groups. The σ^2 is attributed to the farmer-level variation. It explains the within watershed variation.

Results and discussion

Table 2 presents results of the generalized linear mixed-effects model (GLMM). Fixed effects are displayed as odds ratios (OR). The random effects are presented as the watershed-level variation τ_{11} and ICC. The log likelihood and Akaike Information Criteria (AIC) was compared with the null model (with no predictors) and shows considerable improvements in model quality. List-wise deletion of cases led to a reduction in the final sample from 4 778 to 3 574 observations. Listwise deletion removes any respondent in the survey data from the analysis if they did not respond to *any* survey question. The study could select one of several coefficients of determinants or R^2 to present the explained variation in the model. It was decided to use Tjur's D (Tjur 2009) which is a Pseudo R-squared measure suitable for use with a mixed-effects model with a binary outcome. Table 2 shows that the GLMM explains 18% of the variation in the data by including both farmer and watershed level predictors.

The fixed effects are grouped into farmer-level and watershed-level variables. At the farmer-level (level 1), the fixed effects are categorized by predictors such as: (1) farmer identities; (2) risk perceptions, and (2) demographic or control variables. With regard to farmer identities, the 'Productivist' identity was positively and significantly related to farmers' use of precision agriculture. A single standard deviation increase in the 'Productivist' identity is associated with 9% increase in the odds of using precision agriculture (OR=1.09, SE=1.04, p=.06). At the same time, a single standard deviation increase in 'Conservationist' identity improves the odds of using precision agriculture by almost 20% (OR=1.18, SE=1.05, p=.00). This means both Productivist and Conservationist

identities are statistically significant and positively correlated with use of precision agriculture. In addition to these longstanding identities well described in the literature, the relationship between the relatively novel ‘Expert’ and ‘Listener’ farmer identities were examined. The study found that a single standard deviation increase in the Expert identity improves the odds of using precision agriculture by 36% (OR = 1.36, SE = 1.05, $p = .00$). An increase in one standard deviation in the Listener identity improves use of precision agriculture by 11% (OR = 1.11, SE = 1.05, $p = .03$). Consistent with hypothesis H9, the four farmer identity groups are all actively increasing the odds of adopting precision agriculture technologies, with the Conservationist and Expert categories having the strongest impact on adoption decision.

Two significant interactions between farmer identity and land tenure were observed. Results show that farmers were less likely to use precision agriculture if they were ‘Conservationist’ and rented more land than they owned (OR = .68, SE = 1.17, $p = .02$), and if they were ‘Expert’ and owned more land than they rented (OR = .73, SE = 1.12, $p = .00$). Thus, farmers’ likelihood of using precision agriculture could be diminished even if they perceived themselves as ‘Conservationist’ or ‘Expert’.

While studies have shown concerns about general environmental conditions to shape farmers’ intention to use PA (e.g. Watcharaanantapong et al. 2014), this study examines those environmental risk perceptions which directly affect farm productivity and profitability (such as drought and flood). Arguably, these environmental concerns can affect profitability and matter when farmers are making investment decisions for PA. Two out of the four risk perceptions variables were significantly associated with farmers’ use of precision agriculture. These were concerns regarding flooding (*Flood Concern*) and erosion (*Erosion Concern*). This study did not find evidence to support hypotheses H5 (concern about drought) and H8 (concern about climate change). Farmers were more likely to use precision agriculture when they were more concerned about flooding (13% more) (OR = 1.13, SE = 1.04, $p = .00$) (supporting evidence for hypothesis H6) and less likely to use precision agriculture (8% less) when their concerns for erosions were increased by one standard deviation (OR = .92, SE = 1.04, $p = .02$) (inconsistent with hypothesis H7). Thus, concerns about biophysical conditions matter when farmers choose to use precision agriculture. Contrary to previous research that shows variability in availability of water for crops to cause farmers to delay adoption of PA (Higgins et al. 2017), this paper found that concerns about flooding can in fact increase farmers’ propensity to adopt PA. In relation to farmers’ perceived concerns with soil erosion, which this study found to be negatively correlated with farmers’ use of PA, these findings are supported by Isik and Khanna’s (2003) paper, who also found that uncertainty about soil conditions and risk preferences could explain for the low propensity of PA adoption among farmers. It should be noted that Isik and Khanna’s (2003) study is almost 16 years old and recent improvements in PA technologies may have transformed them for aiding farmers to better manage uncertainties surrounding soil conditions. Still, among farmers in this study’s sample, concerns about soil erosion were less likely to drive farmers’ adoption of PA than concerns about flooding. Farmers likelihood to adopt PA still continues to vary by the kind of biophysical factor they deem to be most hazardous to their farm operation.

Several variables related to farm and farmer-related socio-demographic qualities were examined. These include: land tenure, education, diversity in farm enterprise, sales and farm size. Contrary to expectations based on previous research that has shown farmers to use PA when they are concerned about long-term productivity of owned rather than rented land (Watcharaanantapong et al. 2014), this study found that farmers were less likely to use precision agriculture if they *only* owned land (did not own and rent land) (OR = .65,

SE = 1.12, $p = .00$), thus providing evidence to support hypothesis H10. These results contribute to the line of thinking that highlights the need to understand heterogeneity among farmers' land tenure and decisions regarding adopting PA. This paper also found that farmers were more likely to use precision agriculture when they only rented land (compared to owning and renting land) (OR = 1.66, SE = 1.21, $p = .00$). Thus, farmers are more inclined to implement PA technologies even when they do not own the land. One reason could be that PA allows renters to rapidly extract information about land and its characteristics, helping to partially substitute for knowledge commonly held by landowners. Still, most studies (e.g. Prokopy et al. 2008) have found landowners to be strongly motivated to adopt long-term farm strategies that required financial and technical commitments from the farmer. Nevertheless, results here suggest that farmers who only rent land (rather than rent and own land) may be more likely to use PA.

Similar to Tey and Brindal's (2012) work on adoption of PATs, and consistent with hypothesis H3, this study found that educated farmers are more likely to adopt these technologies (OR = 1.23, SE = 1.03, $p = .00$). A possible explanation for this finding is that higher level of education offers possibilities to farmers to more effectively implement PATs that are informationally intensive and analytically rigorous (Tey and Brindal 2012). Indeed, Pavón-Pulido et al. (2017) show that many big agricultural data collection and storage systems require "specialists to be recruited with the aim of controlling and managing such servers". This study also found that farmers who had more than two farm enterprises were more likely to use PA (OR = .75, SE = 1.04, $p = .00$), thus providing evidence for hypothesis H4. Higher farm diversity in the form of greater crop diversity (planting of more than two crops in a year) and integration of livestock into cropping system was positively correlated with farmers use of precision agriculture. An explanation for this result could be that the most agronomically advanced farmers who have decided to introduce a greater number of crops in order to be more efficient environmental and economical (robust) are also more "open" to the use of PA. Besides, having more enterprises suggest that farmers have less time to dedicate to their farm so they must optimize all the actions per crop and PA can assist them with achieving this objective.

Other farm characteristics, such as higher levels of farm size (OR = 1.42, SE = 1.09, $p = .00$) and sales (OR = 1.58, SE = 1.08, $p = .00$) also increased farmers' propensity to use precision agriculture, thus providing support for hypotheses H1 and H2. The results are supported by previous research that found precision agriculture to be more likely to be adopted by farmers managing relatively large farms (Paustian and Theuvsen 2017; Reichardt et al. 2009; Daberkow and McBride 2003; Khanna et al. 1999; Kutter et al. 2011), and who are more likely to use precision agriculture because of their ability to invest in higher fixed costs of such equipment (Khanna et al. 1999) and pay for a specialist or consultant (Kutter et al. 2011).

The study's sampling design was developed to also examine hydrological variations between watersheds and how these asymmetries could be included in understanding farmers' use of various farming practices and techniques, including precision agriculture. Based on the results of the regression, this paper found that watersheds with higher levels of extreme daily and seasonal precipitation events as well as drought may increase farmers' use of precision agriculture by 10 (OR = 1.10, SE = 1.04, $p = .01$), 23 (OR = 1.23, SE = 1.05, $p = .00$), and 16 (OR = 1.16, SE = 1.04, $p = .00$) percent, respectively, thus validating hypotheses H11, H12, and H13. On the contrary, watersheds that had on average, higher percentage of acres categorized as marginal soil could reduce farmers' use of precision agriculture by almost 18% (OR = .82, SE = 1.05, $p = .00$), thus no evidence to support hypothesis H14 was found. Adopting PA has been established as beneficial for "soils with

high slope, heterogeneity, or permeability” (Paustian and Theuvsen 2017). Yet, farmers in the study’s sample who were in watersheds with higher percentage of marginal soil were less likely to use PA. Thus, farmers do not only evaluate the efficacy of PA technology based on its ability to perform well in poor soil conditions (including slope), but their decision likely includes a myriad of other factors, such as social norms, need for large capital investments, and availability of technical support and training, when deciding to adopt PA. For example, social norms concerning which practices and technologies are considered “appropriate” may explain some of the reasoning behind why farmers are more likely to adopt PA in some watersheds. Additionally, it is possible that watersheds with more variation in seasonal weather conditions have retailers or advisors who are more inclined to recommend PA technologies which may contribute to growth of PA users in certain watersheds.

Morton et al. (2015) found that farmers’ decisions to use farming practices and technologies are motivated by spatial and temporal changes in environmental and institutional conditions. This study recognized that such conditions could also be important guides for farmers to use precision agriculture. Therefore, random effects were examined by including a random intercept for each watershed in the generalized linear mixed model (GLMM). Figure 3 shows the random effects by drawing an interval for each watershed. The interval includes a mode at its center and conditional variances to show the confidence around the estimate (mode). Since all the study predictors were centered within context (CWC), the value of the intercept mode can be interpreted as the likelihood of using precision agriculture in each watershed when all predictors are held at their average or mean value. Results show that when all farm and watershed-level predictors are held at their mean value; Middle Platte watershed had the highest and Upper Mississippi Black Root had the lowest intercept. In other words, by holding all predictors at their mean value, respondents who farmed in the Middle Platte watershed were more likely to use precision agriculture than respondents in the Upper Mississippi Black Root watershed. Several reasons can explain the variation in adoption rates between watersheds as witnessed in this analysis. When studying adoption of variable rate technologies, Khanna (2001) argued that closer proximity to technology sellers and larger share of acreage under corn and soybeans (these crops require intensive use of chemical fertilizers) were some of the important reasons for higher adoption of PA in the state of Illinois than in Wisconsin. Thus, institutional factors such as availability of sellers, markets, and policies, can be as important as changes in the environment for affecting farmers’ use of PA. Further research is needed to evaluate the impact of farmers’ social norms and perceived usefulness and acceptance of PA among their social networks, the nature of relationship between farmers and their crop advisors and technology dealers to more comprehensively understand the dynamic changes in adoption of PA across the study region.

Conclusion

Agriculture faces challenges related to climate change and environmental degradation and a precision agriculture approach is widely believed to be solution which, if widely adopted, could support food system resilience. Given its potential benefits, there is incentive for researchers to shed light on why some farmers are more readily adopting PA. There has been substantial literature focusing on this question most of it focusing on the farmer’s demographic characteristics as they relate to adoption. This study’s unique focus is on the

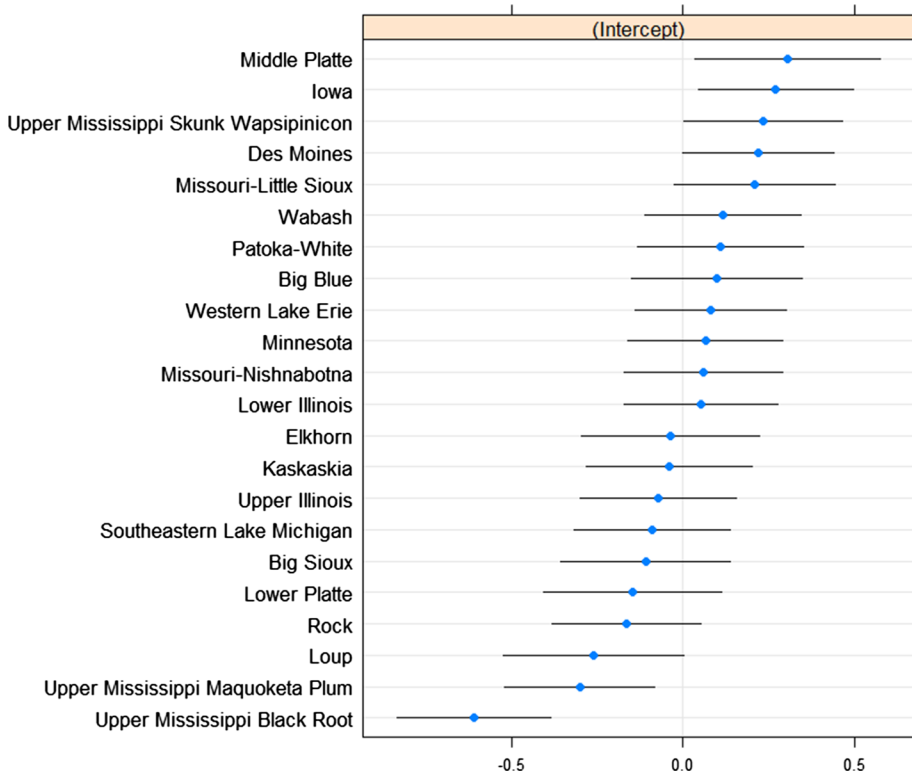


Fig. 3 Random effects displaying the mode and the conditional variances for each watershed

role of Midwestern U.S. farmer identity, their perceptions of environmental, climatic and weather risks, as well as socio-demographic factors as they relate to PA adoption. It was found that all four farmer identity categories used in the analysis—Conservationist, Productivist, Expert and Listener—were active in increasing the odds of adopting PA, with the Conservationist and Expert categories having the strongest positive relationship with adoption. That self-understood environmentalist and conventional farmers were both likely to adopt is an interesting and unexpected finding of this study. This may indicate the efficacy of the dominant framing of PA in corporate promotion and public discourse as a set of tools capable of helping farmers meet environmental as well as economic challenges. A clear message about twined economic and environmental gain has been coming from powerful food system actors such as the United Nations Food and Agriculture Organization (2018) as well as developed country national governments. The European Commission has funded the Internet of Food and Farming 2020 with the goal to foster uptake of precision agriculture (n.p./online) as one “vital step towards a more sustainable food value chain. With the help of IoT technologies higher yields and better-quality produce are within reach. Pesticide and fertilizer use will drop and overall efficiency is optimized” (n.p./online). The findings may also suggest that PA is being perceived by farmers as a process of reconciling their short-term productivist goals with long-term conservation goals. Interestingly, the study’s results suggest that conventional agriculture may be witnessing the emergence of social identities that are *shaped* by the adoption of PA itself. These identities are fluid and

based not only on traditional values (e.g. land ethic) but also based on farmer's knowledge and expertise of these novel technologies.

Several limitations of the study require carefulness in drawing conclusions. First, the measure of PA adoption used here have limitations. The single-item survey measure used to study PA adoption lumps very distinct PA technologies, including GPS, GIS, and variable-rate technology into one question. Instead, using a single question for each PA technology may provide a more robust understanding of which technology is more widely adopted among farmers, how these technologies are used within the farm, and whether using certain PA technologies influence decisions pertaining to other farm (agronomic and financial) management aspects. It is recommended that future research could examine the potential cascading effect of PA adoption, specifically how use of one PA technology can influence farm operators to change other farming decisions too. Furthermore, there are some limitations with using HUC6 watershed as the study's secondary level of analysis. While there is considerable homogeneity in biophysical conditions at this level, there may be further unexplained variation within these watersheds. For instance, soil conditions at the farm level vary widely not only within a watershed, but also can change drastically at the field-level. Future research could address this sub-spatial concern by adding a third level to the analysis—by incorporating soil and weather conditions at the farm level.

Limitations aside, the study findings suggest the need for other studies which integrate identity and environmental risk-perception variables into the study of PA adoption. Despite the large sample size which spans several watersheds across the Midwestern U.S. (see Fig. 2), the statistical model of this study ought to be replicated in other jurisdictions—for instance among farmers more likely growing horticultural (versus agronomic) crops and in other geographic locale. Additional survey work could examine the role of different understandings of PA as they influence not just adoption of digital technologies but also farmers' use of best management practices at large, including those that may be climate resilient and/or improve water quality. Such research would be of value to academic communities as disparate as agricultural economy and media studies but also to industry and governance actors making crucial decisions on which technologies to support for sustainable food systems as well as how to promote the adoption of such tools.

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