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Adoption of Precision Agriculture for Cotton in the Southern United States

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A nested logit model was applied to the 2009 Southern Cotton Precision Farming Survey to study the influence of farmer and farm characteristics on the adoption of Variability Detection Technologies (VDTs) and Variable Rate Application Technology (VRT). The results reveal that farm size, ownership of the land, and exposure to Extension activities are important factors affecting the choice of VDTs. Also, the farmers adopting both soil-based and plant-based VDTs were found to be more likely to adopt VRT. The probability of adoption of VRT was found to be lower for Texas cotton farmers compared to those in other surveyed states, regardless of the type of VDT adopted.

Key words: cotton, precision agriculture, technology adoption

Precision Agriculture (PA) is a management practice that aims at enhancing crop productivity by matching resource application and agronomic practices to the spatial and temporal variability in field conditions and crop requirements (Whelan and McBratney, 2000). Site-specific management of crops, at least informally, has been going on since the dawn of agriculture. In the past, producers operated smaller farms and did their best to match the input application with the crop requirements by applying more fertilizers in areas with lower fertility or by resorting to spot application of pesticides only in infested areas of the field. But with the advent of mechanization, driven by economies of size, producers started operating much larger farms in fields managed with uniform agronomic practices. However, these practices generally overlooked the spatial variability within the farm-field, potentially reducing the agronomic and economic efficiency of the farm.

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Recent technological advances such as Differential Global Positioning Systems[1] (DGPS) and the Real-Time Kinematic[2] (RTK) systems along with improvements in Geographical Information System (GIS) and remote sensing technologies have enabled farmers to identify and quantify the within-field variability and to adjust management practices accordingly with considerable precision (Batte and Ehsani, 2006).

The main components of PA are the collection and processing of field variability information, and variable rate application of inputs (Blackmore, Godwin, and Fountas, 2003). The data collection and processing methods are used to identify and quantify the variability in soil fertility or crop growth within a field. In this article, we denominate these practices as Variability Detection Technologies (VDTs). Examples of VDTs are zone soil sampling, grid soil sampling, electrical conductivity measurements, yield monitors, aerial imagery, and satellite imagery. Once field variability data are collected and analyzed, the appropriate management responses are provided that may include application of inputs at variable rates. After the analysis of field variability data, the field is generally delineated into homogeneous management zones, according to the extent and spatial distribution of variability, for which a single rate of a specific crop input is appropriate (Doerge, 1998). Variable Rate Technology (VRT) refers to a system combining a computer capable of controlling input application rates with the application equipment to achieve input applications at the prescribed rates in various parts of the field (Khanna, Epouhe, and Hornbaker, 1999)

[1] Differential Global Positioning System (DGPS) is an enhancement to GPS to improve its accuracy from about 15 meters in case of normal GPS to about 10 centimeters in case of DGPS. DGPS uses corrections to the satellite GPS signal from a fixed reference station for which the location is known with high accuracy. In some regions, networks of such fixed reference stations have been established so that a user of DGPS does not have to set up their own reference station. The correction signal from a reference station is typically broadcasted using ground-based radio transmitters that serve the local area around the reference station. The DGPS includes a radio receiver for these signals, and uses the transmitted information to correct the GPS signal received directly from the satellites. This significantly improves the accuracy of position estimates.

[2] Real Time Kinematic (RTK) systems used in GPS is a type of DGPS that can provide position information for moving vehicles with sufficient accuracy and frequency to allow the vehicles to be autonomously guided by the GPS signal. RTK GPS makes use of real-time corrections provided by a reference station, resulting in centimeter-level position accuracy. Ordinary GPS compares the signal sent from the satellite with an internally generated copy of the same signal. Since the signal from the satellite takes time to reach the receiver, the two signals are not coherent since the satellite's copy is delayed in relation to the local copy. In RTK GPS, the reference station receives the signal from the satellite and re-broadcasts the phase of the carrier that it measured. The mobile unit then compares its own phase measurements with the ones received from the reference station. Real-time positions can be calculated as fast as 20 times per second to provide centimeter level accuracy. RTK GPS has primarily found application in the guiding of agricultural and construction vehicles, such as tractors, harvesters, and road construction equipment.

This use of spatial information in input application provides several potential advantages to managing crop production using PA, including higher crop yields, more efficient use of resources like seeds, irrigation water, fertilizers and other agrochemicals, and reduction of potential negative environmental impacts of harmful agricultural chemicals (Pierce and Nowark, 1990). Besides these benefits, adoption of some technologies like yield monitors is also useful for record-keeping and documentation, providing detailed information about the location of the crops planted and the corresponding yield during each season (Lowenberg-DeBoer and Erickson, 2000).

In spite of these potential advantages, the worldwide adoption of PA is considerably low (Daberkow and McBride, 2003; Daberkow, Fernandez-Cornejo, and Padgitt, 2002; Lowenberg-DeBoer, 1999; Reichardt et al., 2009; and Reichardt and Jurgens, 2009). The adoption rate among U.S. cotton farmers is even lower (Daberkow and McBride, 2000), although the United States is a major producer and exporter of cotton with an estimated harvested area of 10.4 million acres and production of 18 million bales in 2010 (USDA, 2010). A nationwide survey conducted in 1998 indicated that 70% of the farmers in the United States were not even aware of the existence of precision farming technologies (Daberkow and McBride, 2000). Roberts et al. (2002) reported that only 23% of the cotton producers who responded to the 2001 Southern Cotton Precision Farming Survey adopted at least one of the PA techniques. The Agricultural Resource Management Survey (ARMS), U.S. Department of Agriculture (USDA, ARMS, 2011), estimated that yield monitor was used in only 4.71% and VRT for application of any kind of fertilizers was used only in 4.46% of the planted acres of cotton in the United States in 2007.

The relatively low level of adoption of PA is attributed to different technological and socio-economic factors. First of all, adoption of PA is markedly different from adoption of other innovations in agriculture. For example, to adopt a pest-resistant crop variety, the farmer simply uses the purchased seeds. But, there is a learning process involved in the case of adopting PA (Lowenberg-DeBoer, 2003). Considerable investments in time and effort are usually required to learn how to use new technologies. Researchers generally agree that the lack of demonstrated evidence for the economic advantages of adopting PA, uncertainty in returns from adoption, high fixed cost (Khanna, Epouhe, and Hornbaker, 1999), farmers' lack of awareness of the existing PA technologies in the market (Daberkow and McBride, 2000), and difficulty in understanding the technologies and interpreting the data (Reichardt and Jurgens, 2009) are the main deterrents of widespread adoption of PA.

Since PA is a response to the within-field spatial variability in soil characteristics or crop productivity, the profitability from adopting PA technologies is also largely dependent on the extent of variability in soil or topographic characteristics within the field (Roberts, English, and Mahajanashetti, 2000). Hence the incentive to adopt PA may vary from farm to farm, which may cause considerable variability in its adoption pattern. Considering this difference in adoption patterns, the multitude of bottlenecks in adoption of PA, and the potential economic and environmental benefits of PA, it is important to study the factors affecting a farmer's adoption of PA.

Although the adoption of individual VDTs and VRT has been extensively studied (Daberkow and McBride, 2003; Larson et al., 2008; McBride and Daberkow, 2003; Walton et al., 2008; and Walton et al., 2010), not much is known about how the adoption of one affects that of the other. The few studies dealing with adoption of VRT for farmers adopting any VDT (Khanna, 2001; and Roberts et al., 2004) considered a single VDT and analyzed the relationship between adoption of that VDT and adoption of VRT.

Adoption of VDTs is a prerequisite for adoption of VRT, but it is generally observed that the majority of farmers do not adopt VRT even after adopting one or more types of VDTs. For example, in Brazil the adoption rate of VRT is very low despite the high adoption rate of yield monitors (Lowenberg-DeBoer, 1999). Khanna, Epouhe, and Hornbaker (1999) also reported that most of the farmers decide not to adopt VRT even after adopting one or more types of VDT, which indicates that different driving forces may be responsible for adoption of VDTs and VRT. Moreover, while plant-based VDTs are suitable for variable rate application of plant growth regulators or pesticides in cotton, soil-based VDTs are more suitable for application of fertilizers or soil amendments at variable rates. Hence there may be a difference in the probability of adoption of VRT among the farmers who adopt different types of VDTs. The objectives of this study are 1) identify the different factors affecting the adoption of VDTs and VRT; 2) identify whether the adoption probability of VRT depends on the particular type of VDT chosen; and 3) compare the adoption pattern of VDTs and VRT in Texas with that in other surveyed U.S. states.

Objective three is important because, despite being the largest cotton producing state in the United States with 48% of the harvested area and 40% of cotton production, Texas had not been included in the previous Southern Cotton Precision Farming Surveys. Hence this analysis can provide new knowledge of the adoption pattern of PA in Texas and how it differs from that in other cotton-producing states.

Understanding the adoption patterns of various PA technologies can be useful to researchers, Extension agents, and agro-industries. It provides insights into the role of farm and farmer characteristics that influence the diffusion of these technologies. Such information can be used to develop new research initiatives to satisfy the unique needs of a farming community, and help design better Extension strategies to disseminate specific technologies for the targeted farms and farmers.

Econometric Model

As highlighted earlier, the adoption of VDTs and VRT may be influenced by different factors and the adoption of VRT may depend on the type of VDT chosen by the decision maker. Using the nested logit model, we structure the adoption decision in two levels: the first is the choice of the type of VDT, and under each type of VDT adopted is the second level of decision on the adoption of VRT. This allows the use of different explanatory variables at different levels of decision making and provides a direct estimate of the conditional probabilities of adoption of VRT for farmers adopting different groups of VDTs. Hence a nested logit model serves as the ideal tool to study the factors influencing the choice of a specific group of VDTs and those affecting the adoption of VRT under each group of VDT.

The nested logit model does not rely on the restrictive Independence of Irrelevant Alternatives (IIA) assumption, as in the case with more commonly used mixed logit models. Further, since the nested logit is a Random Utility Model (RUM), it assumes that individuals make choices that maximize utility, which is composed of an observable component (expected utility) and an unobservable component (stochastic error term). The conceptual framework of the nested logit model is described below (McFadden and Manski, 1981; and Train, 2003).

Let $T = \{1,2,3,4\}$ be the set of indices denoting the first level of choices. Let the bottom level choices, which are the mutually exclusive set of integers representing the available choice set, be S_t, where $t \in T$. Following the RUM, let $U_{tj} = V_{tj} + \varepsilon_{tj}$, where $j \in S_t$. Then the error term has a Gumbel distribution as illustrated below in equation (1).

$$F(\epsilon) = \exp\left(-\sum_{t \epsilon T}\left[\sum_{j \epsilon S_t} \exp\left(\frac{-V_{tj}}{\rho_t}\right)\right]^{\rho_t}\right) \qquad (1)$$

where $\rho_t = \sqrt{1 - Corr[\varepsilon_{tj}, \varepsilon_{tk}]}$ is the scale parameter (Cameron and Trivedi, 2005).

The linear predictor V_{tj} is assumed to be decomposed into the sum of the product of coefficients and explanatory variable vectors in the two levels as shown in equation (2).

$$V_{tj} = A_t \alpha_t + B_{tj} \beta_j \qquad (2)$$

where A_t and B_{tj} are the row vectors of explanatory variables in the first and bottom level respectively, and α_t, and β_j are the corresponding column vectors of regression coefficients.

The probability of level 1 choice C_1 and level 2 choice C_2 can be written as equation (3) and (4) respectively.

$$\Pr(C_1 = t) = \frac{\exp(A_t\alpha_t + \nu_t J_t)}{\sum_{t\epsilon T}\exp(A_t\alpha_t + \nu_t J_t)} \tag{3}$$

$$\Pr(C_2 = j|C_1 = t) = \frac{\exp\left(\frac{C_{tj}\gamma_j}{\rho_t}\right)}{\sum_{j\epsilon S_t}\exp\left(\frac{C_{tj}\gamma_j}{\rho_t}\right)} \tag{4}$$

where J_t is called the inclusive values or log-sums for the first level given by equation (5).

$$J_t = \log\sum_{j\epsilon S_t}\exp\left(\frac{C_{tj}\gamma_j}{\rho_j}\right) \tag{5}$$

Let index $i = 1, \ldots, N$ (where N is the sample size) indicates individual farmers, so that y_{itj} indicates that individual i has chosen the t^{th} alternative in the first level, and j^{th} in the second level. The estimation of a nested logit model is conducted using the following log likelihood function:

$$LL = \sum_{i=1}^{N}\sum_{t\epsilon T}\sum_{j\epsilon S_t} y_{itj}\,\{A_{it}\alpha_t + \rho_t J_{it} - \log(\sum_{t\epsilon T}\exp(A_{it}\alpha_t + \rho_t J_{it}))\} \tag{6}$$

$$+B_{itj}\beta_j|\rho_t - \log\sum_{j\epsilon S_t}\exp B_{itj}\beta_{jk}|\rho_t$$

Data and Empirical Model

The data for this study was extracted from the 2009 Southern Cotton Precision Farming Survey. A detailed description of the methods adopted and general findings of this survey can be found in Mooney et al. (2010). A total of 1, 692 surveys were returned for a response rate of 12.5% from cotton farmers in 12 southern U.S. states (Alabama, Arkansas, Florida, Georgia, Louisiana, Missouri, Mississippi, North Carolina, South Carolina, Tennessee, Texas, and Virginia). Apart from questions related to the status of adoption of PA practices, the survey respondents provided information about themselves, the characteristics of their farms, and the farming practices adopted on the farms. This is the first time that the survey included Texas, which may have a different adoption pattern compared to other southern states owing to the table-top topography of its major cotton-producing region (Texas High Plains). The large number of responses from Texas permits comparison of the adoption pattern between Texas and other surveyed states.

The responses to questions concerning the VDTs adopted by the farmers in the survey were used to group the VDT adoption into four mutually exclusive and exhaustive groups. The first group consists of the adopters of only soil-based VDTs such as grid soil sampling, zone soil sampling, use of electrical conductivity maps, and use of soil survey maps. The adopters of only plant-based VDTs such as yield monitor, aircraft imagery, and satellite imagery are included in the second group. The third group represents the adopters of both soil-based and plant-based VDTs. Those who did not adopt any of these VDTs constituted the fourth group. These four groups were designated as soil, plant, both, and none, respectively, in the nested logit model. The farmers adopting VRT for application of any inputs (fertilizers, lime, water, growth regulators, etc.) were considered as adopters of VRT and were designated as y in the nested logit model and the non-adopters of VRT were designated as *n*.

After rearranging the respondents from the survey into four groups based on adoption of VDTs and two groups based on the adoption of VRT, the resulting data was analyzed using a nested logit model with two levels. The first level divides VDT adoption into four groups, namely *soil, plant, both*, and *none*. The second level divides the farmers who chose each of these groups into adopters and non-adopters of VRT (*y* and *n*). The tree structure of the nested logit model used in the study is presented in Figure 1.

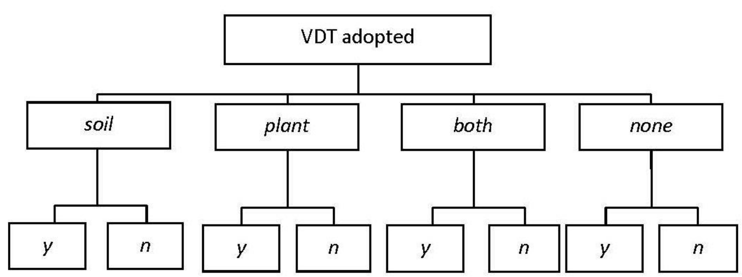

Figure 1. Tree structure of the nested logit model used in the study.

Note that the tree structure does not necessarily imply sequential decision-making by the farmer. The farmer chooses one alternative from the set of available choices, which is also known as the bottom alternative set, and the choices are grouped to arrive at the tree structure. The structuring of the decision-making sequence is by construction of the tree structure of the model to analyze the conditional probabilities of decisions in the second level given that the farmer already made a decision in the first level. The choice set with the description of choices is provided in Table 1.

Table 1. Definition of the choice set in the nested logit analysis

No.	Choice	Definition
1	*noney*	The farmer adopted none of the given VDT & adopted VRT
2	*nonen*	The farmer adopted none of the given VDT & did not adopt VRT
3	*soily*	The farmer maker adopted soil-based VDT & adopted VRT
4	*soiln*	The farmer maker used soil-based VDT & did not adopt VRT
5	*planty*	The farmer maker used soil-based VDT & adopted VRT
6	*plantn*	The farmer maker used soil-based VDT & did not adopt VRT
7	*bothy*	The farmer used both plant and soil-based VDT & adopted VRT
8	*bothn*	The farmer adopted both plant and soil-based VDT& did not adopt VRT

The survey responses provided information on the farm and farmer characteristics. This information, together with the farm's location, provides the data used as independent variables that may influence the adoption of VDT, VRT or both.

There are a number of previous studies that reports the negative impact of age of the farmer (Akridge and Whipker, 1999; Batte and Johnson, 1993; Fernandez-Cornejo, Beach, and Huang, 1994; Larson et al., 2008 ; Sevier and Lee, 2004; and Walton et al., 2010) and ownership of the farm (Daberkow and McBride, 2003) and positive impact of the level of education of the farmer (Akridge and Whipker, 1999; Fernandez-Cornejo, Beach, and Huang, 1994; Larson et al., 2008; and McBride and Daberkow, 2003), exposure to computers (Daberkow and McBride, 2003; and Walton et al., 2010), awareness about the existence of new technologies (Daberkow and McBride, 2003), and farm size (Daberkow and McBride, 2003; Just, Zilberman, and Rausser, 1980; Larson et al., 2008; Reichardt and Jurgens, 2009; and Walton et al., 2010) on the adoption of different PA technologies. The differences in adoption of PA among different geographical locations were also recognized by several previous researchers (Daberkow and McBride, 2000; Daberkow and McBride, 2003; and Lowenberg-DeBoer, 1999).

Considering the possible influence of these important variables on the adoption of PA, we used the age of each farmer (*age*), number of years of formal education (*edu*), use of computers for farming operations (*comp*), exposure to Extension publications (*ext*), farm size (*area*), and percent of the farm owned by the farmer (*perown*), and a dummy variable (*texas*) to distinguish the farms located in Texas from those in other surveyed states as the independent variables in this study. All the explanatory variables used in the study and their definitions are provided in Table 2.

Table 2. The definition of the explanatory variables analyzed.

Variable Name	Definition
age	Age of the decision maker in years
edu	Number of years of formal education of the decision maker discarding the kindergarten (preschool) education.
comp	Dummy variable that assumes the value of 1 if the farmer uses computers for farming operations and 0 otherwise
ext	Dummy variable that assumes the value of 1 for the farmer who attended Extension seminars or uses Extension publications and 0 otherwise
area	The average area planted to cotton during 2007 and 2008 in acres
perown1	Percentage of the area cultivated that is owned by the farmer is less than 33.33 %
perown2	Percentage of the area cultivated that is owned by the farmer is between 33.33 and 66.66 %
perown3	Percentage of the area cultivated that is owned by the farmer is less than 66.66 %
texas	Dummy variable that assumes the value of 1 if the farm is located in Texas and 0 otherwise

The nested logit model requires a unique set of explanatory variables to influence the decision making at different levels of the nest. The major plant-based VDTs are more responsive to farm size than the soil-based VDTs. For example, cotton yield monitor is highly capital intensive and, hence, the non-divisibility of the technology makes the adoption profitable for farmers having farm size greater than a critical limit (Just, Zilberman, and Rausser, 1980). The other two technologies in this group—satellite imagery and aircraft imagery—are also more suitable for farmers operating larger farms. Similarly, Extension publications are generally regarded as the instruments to increase the awareness of farmers and, hence, are more likely to influence choice of VDTs that are less technologically intensive than VRTs, which require higher technological and capital inputs (Daberkow and McBride, 2003). The farmers operating rented farms are generally full-time farmers who are more aware of the technological innovations (Daberkow and McBride, 2003), but are likely to adopt technologies that are less capital intensive. Hence, area, *ext*, and *perown* are hypothesized to influence the choice of VDT from the available groups. The remaining variables—*age, edu, comp*, and *texas*—were hypothesized to influence the adoption of VRT for farmers in each group of VDT adoption because our objective was to estimate the impact of these important factors on adoption of VRT for farmers adopting different groups of VDTs.

The nested logit model was estimated in STATA®, which also was used to estimate the predicted probabilities of adoption at each level of the model, and the conditional probabilities for adoption of VRT for farmers adopting each group of VDT.

The low response rate of the survey resulted in a bias in data towards larger farms (Jenkins et al., 2011). Missing values in some explanatory variables resulted in further removal of about 13% of the total of 1,692 observations. This suggests the sample may not be representative of the population of cotton farmers in the region. Post-stratification weights, based on the 2007 agricultural census, were used to address this issue. The observations were grouped into 72 classes corresponding to the 12 states and six acreage classes. The acreage classes were based on the area planted to cotton during 2007 and the classes were 1-99; 100-249; 250-499; 500-999; 1,000-1,999; and 2,000 or more. After grouping the observations to these strata, the weights were estimated using two different methods discussed in more detail by Harper et al. (2010) and Jenkins et al. (2011). In the first method, weights were estimated by adjusting the observations in the sample in each group with that in the census. The raking procedure suggested by Brackstone and Rao (1976) was the second method used to estimate the weights. The estimation of the model was done using data with these two types of weights and without weights.

Results and Discussion

The frequency analysis of the adoption percentages in the data showed that 2.87% of the farmers adopted only plant-based VDTs, 21.71% adopted only soil-based VDTs, and 7.37% adopted both soil-based and plant-based VDT. The average predicted probabilities for adoption of plant-based, soil-based, and both plant-based and soil-based VDTs were 0.0290, 0.2171, and 0.0741, respectively, which are close to the values indicated by the frequency analysis of the data demonstrating a good fit of the model. Among the farmers who adopted both soil-based and plant-based VDT, 67.59% adopted VRT, whereas the adoption percentage of VRT was 35.85% and 28.67%, respectively, for farmers adopting soil-based and plant-based VDT. The predicted probability of adoption of VRT were 58.21, 40.32, and 33.73 for the farmers who adopted both soil- and plant-based VDTs, soil-based VDTs and plant-based VDTs, respectively.

These results indicate two different features of the adoption process. The first feature is that the majority of the farmers did not adopt VRT even after adopting some form of VDT. Such limited adoption behavior was observed by several other researchers. Khanna, Epouhe, and Hornbaker (1999) observed this limited adoption behavior among cash grain farmers in Iowa, Illinois, Indiana, and Wisconsin where the farmers chose to adopt VDT but preferred to wait further before adopting VRT. Lowenberg-DeBoer (1999) reported that the adoption rate of VRT is very low in Brazil despite the high adoption rate of yield monitors. Grenadier and Weiss (1997) showed the uncertainties about the accuracy of the technology and anticipation about possible advances in the technology to be the major reasons for this limited adoption behavior. Moreover, since the benefits of adoption of PA depend on the within-field variability of the farm, the potential benefits for a particular farm is uncertain. Leathers and Smale (1991) demonstrated that this uncertainty can be a reason for farmers to adopt only some parts of the PA technology instead of adoption of PA in its entirety.

The second feature is the differences in the adoption rate of VRT among farmers who adopted different groups of VDTs. The data indicated higher levels of adoption of VRT for farmers adopting both soil- and plant-based VDTs and lower levels of adoption for those adopting only plant-based VDTs. Different soil properties interact in a complex way, which manifest in the variability of the crop yield. Plant-based VDTs provide information only about the variability in plant growth or crop yield, but do not provide any information about underlying yield-limiting factors. The yield in different parts of the field may be limited by different factors, which may create difficulty in making VRT decisions based solely on plant-based VDTs. This may be a possible reason for lower adoption of VRT among farmers adopting only plant-based VDT. Soil-based VDTs can provide information on soil factors and their variability, which substantiate the increased percentage of adoption of VRT among adaptors of soil-based VDT. However, the yield-limiting factor may vary within and between the growing seasons (Plant, 2001). The use of both soil- and plant-based VDT provide the information on both soil characteristics and plant growth and, thereby, provide a reasonably accurate indication of the input to which the crop is responding. This explains the higher observed use of both soil- and plant-based VDTs by the adopters of VRT.

Adoption of VDTs

The coefficient estimates for the variables hypothesized to influence the adoption of VDTs are presented in Table 3. As expected, farm size had a positive and significant impact on the adoption of plant-based VDT. This positive effect of the farm size on the adoption of yield monitors was reported by several researchers (Daberkow and McBride, 2003; Just, Zilberman, and Rausser, 1980; and Reichardt and Jurgens, 2009). A cotton yield monitor is the major plant-based VDT, which is a capital-intensive technology and hence can be efficiently adopted only by producers operating larger farms. The non-divisibility of the technology is likely to discourage adoption by decision makers having farm sizes below a critical limit since adoption requires equipment that may be profitable to use only in farms larger than the critical limit (Just, Zilberman, and Rausser, 1980). Moreover, the other two VDTs grouped as plant-based VDT (aircraft imagery and

Table 3. Estimated coefficients for adoption of VDT

VDT	Variable	No Weights			Proportional Weights			Raking Weights		
		Coeff.	SE	P>|z|	Coeff.	SE	P>|z|	Coeff.	SE	P>|z|
both	*area*	0.000684	0.000104	<0.001	0.000818	0.000114	<0.001	0.00082	0.000116	<0.001
	ext	0.834	0.27	0.002	0.842	0.276	0.002	0.848	0.268	0.002
	perown2	-0.128	0.352	0.716	-0.387	0.361	0.284	-0.36	0.356	0.312
	perown3	-0.817	0.268	0.002	-0.881	0.282	0.002	-0.854	0.281	0.002
soil	*area*	0.000125	9.15E-05	0.171	0.000118	0.000112	0.294	0.000138	0.000109	0.207
	ext	0.684	0.149	<0.001	0.805	0.175	<0.001	0.78	0.17	<0.001
	perown2	-0.08	0.278	0.747	-0.197	0.291	0.5	-0.155	0.287	0.589
	perown3	-0.176	0.175	0.315	-0.28	0.205	0.171	-0.334	0.204	0.101
plant	*area*	0.000369	0.000158	0.02	0.000383	0.000192	0.046	0.000386	0.000202	0.056
	ext	0.589	0.347	0.089	0.972	0.415	0.019	0.771	0.393	0.05
	perown2	-0.845	0.533	0.113	-1.068	0.563	0.058	-0.976	0.556	0.079
	perown3	-1.017	0.346	0.003	-1.168	0.428	0.006	-1.045	0.413	0.011
	None	Base								
LL / log pseudolikelihood		-1686.42			-16818.25			-16824.42		
Wald χ^2		470.11			493.29			562.9		
$p > \chi^2$		<0.001			<0.001			<0.001		

satellite imagery) are also more ideal to farmers operating larger farms. Specifically, the adoption of aircraft imagery requires capturing the image of the field with a modified aircraft (service often provided by consultants), where economies of scale is very important. Another argument in favor of the higher likelihood of adoption in larger farms is that the larger farms are agronomically more inefficient compared to smaller farms because they may have higher within-field variability (Kramer, 1987); hence, the benefits from adoption of PA will also be higher in larger farms.

However, it is important to note that farm size did not significantly influence the adoption of soil-based VDT. The major VDTs included in this group were grid soil sampling, zone soil sampling, and electrical conductivity measurements. The adoption of these VDTs may not depend on the size of the farm because the number of soil samples taken is generally decided on a per-acre basis taking into account the within-field variability. Hence, the cost of data collection increases with an increase in farm size and the extent of variability within the field. This result contradicts the findings of Walton et al. (2010) that farm size is a significant factor influencing the adoption of soil grid sampling. One reason for the deviation of our results from that of Walton et al. (2010) may be the inclusion of Texas data in our study, which has a significant number of less intensively managed, large cotton farms with considerably low within-field variability.

The choice to adopt both soil- and plant-based VDT was positively and significantly influenced by farm size, evidently because of the economies of scale and the potential relationship of the benefits of adoption of PA with farm size and within-field variability.

The exposure of farmers to university Extension activities was found to have a positive impact on the adoption of soil-based VDT, and both soil- and plant-based VDT. Even though the analysis of the data without weights indicated the impact of exposure to university Extension activities on the adoption of plant-based VDT to be not statistically significant at 5% alpha level ($p >|z|= 0.89$), the analysis with both proportional weights and weights derived using the raking procedure showed a significant effect for farmers adopting plant-based VDT also. The soil-based VDTs do not require a large initial investment, as is the case of plant-based VDTs like yield monitors, and are not influenced much by farm size. This may be the reason for Extension activities to significantly influence the adoption of soil-based VDT, while having no impact on the adoption of plant-based VDTs. As suggested by Daberkow and McBride (2003), exposure to Extension activities influenced the adoption of PA technologies by increasing the awareness about the existence of that technology.

The results also indicate that the percentage of cropped area owned by the farmer significantly and negatively influence the choice of the VDT. However, the impact of the percentage of cultivated area owned by the farmer did not significantly influence the adoption of soil-based VDT. The producers who farm leased land are generally identified to be full-time farmers who are ready to spend more time farming to make it profitable, and who are generally perceived to be adopters of technologies that enhance profit. This substantiates the observed higher level of adoption of VDTs by farmers who own a lower fraction of the farmed area. Daberkow and McBride (2003) reported a similar finding that most of the adopters of PA are full-time producers who farmed mostly rented lands.

Table 4. Average marginal impact of variables on adoption of VDTs

VDT	Variable	Average Marginal Impact		
		No weights	Proportional weights	Raking weights
Both	*area*	4.56E-05	4.82E-05	4.97E-05
	ext	0.052	0.045	0.047
	perown2	-0.007	-0.021	-0.020
	perown3	-0.054	-0.050	-0.054
Soil	*area*	1.91E-05	1.69E-05	2.06E-05
	ext	0.128	0.148	0.143
	perown2	-0.013	-0.033	-0.025
	perown3	-0.027	-0.046	-0.072
plant	*area*	9.62E-06	1.06E-05	1.03E-05
	ext	0.015	0.027	0.020
	perown2	-0.024	-0.032	-0.028
	perown3	-0.028	-0.034	-0.031
None		Base		

The estimated average marginal impacts of the variables on the probability of different groups of the VDT are provided in Table 4. These results show that the average marginal impact of the farm size on the adoption of all groups of VDTs is very small. A hundred-acre increase in farm size is predicted to increase the probability of adoption of plant-based VDT by 0.00096 and that of both soil- and plant-based VDT by 0.0045 only. The probabilities of adoption of soil-based VDT, plant-based VDT, and both soil- and plant-based VDT are respectively 0.128, 0.015, and 0.052 higher for the farmers utilizing university Extension activities. The farmers who own more than 66.66% of the land they are farming have a 0.024 lesser probability of adopting soil-based VDT and a 0.054 lesser probability adopting both soil- and plant-based VDT compared to farmers who own less than one-third of the total area farmed.

Adoption of VRT

The coefficient estimates for the adoption of VRT for famers choosing each group of VDT is provided in Table 5. The age of the decision maker has a significant and negative impact on the adoption of VRT for farmers choosing only soil-based VDT and both soil- and plant-based VDT. The higher probability of adoption of PA technologies by younger farmers was found by several other researchers (Daberkow and McBride, 2000; Daberkow and McBride, 2003; Larson et al., 2008; and Walton et al., 2010). The higher level of adoption of new technologies by younger farmers can be attributed to the availability of a longer planning horizon that lead to a lower level of risk aversion for younger farmers (Batte and Johnson, 1993; and Sevier and Lee, 2004). Moreover, younger farmers generally have less experience and familiarity with conventional technologies and hence are more likely to adopt PA technologies.

The education of the decision maker is another factor that was found to significantly influence the adoption of VRT. The impact of education on the adoption of VRT was significant only for farmers adopting both soil- and plant-based VDT. This shows that more educated farmers resort to more than one type of technology to assess the within-field variability. Most of the technology adoption studies have reported the decision makers' education to be an important factor influencing adoption of PA (Akridge and Whipker, 1999; Batte and Johnson, 1993; and Sevier and Lee, 2004). This positive impact of education is likely to be due to the educated farmers' better awareness about the existence of newer technologies (Daberkow and McBride, 2003). Another factor that can be responsible for this result is that the higher knowledge level of the educated farmers may result in better understanding of new technologies. Moreover, higher education levels also indicate the possibility of having better learning skills and so will help farmers learn new practices with ease.

Table 5. Estimated coefficients for adoption of VRT

VDT	VRT	Variable	No Weights			Proportional Weights			Raking Weights		
			Coeff.	SE	P>|z|	Coeff.	SE	P>|z|	Coeff.	SE	P>|z|
both	*yes*	*age*	-0.077	0.038	0.043	-0.082	0.045	0.068	-0.067	0.038	0.074
		edu	0.347	0.152	0.022	0.271	0.132	0.040	0.260	0.119	0.030
		comp	2.801	1.579	0.076	3.604	2.705	0.183	2.631	2.387	0.270
		texas	-8.785	3.587	0.014	-8.023	4.538	0.077	-6.929	4.372	0.113
	no	Base									
soil	*yes*	*age*	-0.124	0.522	0.017	-0.107	0.071	0.134	-0.085	0.059	0.150
		edu	0.213	0.137	0.121	0.028	0.028	0.843	0.022	0.130	0.865
		comp	3.584	1.439	0.013	5.373	5.373	0.039	4.239	2.104	0.044
		texas	-10.100	3.465	0.004	-9.042	-9.042	0.014	-8.729	3.886	0.025
	no	Base									
plant	*yes*	*age*	-0.077	0.047	0.105	-0.074	0.054	0.169	-0.044	0.046	0.336
		edu	0.181	0.178	0.309	0.252	0.267	0.345	0.117	0.172	0.496
		comp	3.446	2.067	0.096	2.752	2.600	0.290	2.361	2.727	0.387
		texas	-3.090	2.051	0.132	-3.370	3.870	0.384	-1.889	3.130	0.546
	no	Base									

Even though the use of computers for farming operations significantly influenced the adoption of VRT for farmers adopting soil-based VDT at 5% alpha level, computer use for farming operations have a significant impact on the adoption of VRT for farmers adopting soil-based VDT and both soil- and plant-based VDT at 10% alpha level. The use of computers in farming operations was found to be a significant determinant of the adoption of PA by several other researchers (Daberkow and McBride, 2003; and Walton et al., 2010). Since VDTs require the use of computers for analyzing the data and arriving at variable rate application maps, computer-savvy farmers could find it easier to acquire the necessary skills to use VDTs, thus leading to a higher likelihood of adoption.

The results presented in Table 3 also indicate that the Texas cotton farmers who adopted either soil-based VDT or both soil- and plant-based VDT are less likely to adopt VRT compared to the cotton farmers in other surveyed southern U.S. states. The possible reason for lower adoption of VRT in Texas may be the lower inherent within-field variability in the Texas High Plains, which accounts for 69% of the cotton acreage and 75% of production in Texas (USDA, National Agricultural Statistics Service, 2010) and the presence of a large number of dryland cotton farms in Texas that are less intensively managed. The difference in the adoption rate of PA among geographical locations was reported by several other researchers (Lowenberg-DeBoer, 1999; Daberkow and McBride, 2000; and Walton et al., 2010).

The estimated average marginal impacts of the variables on the probability of adoption of VRT for farmers choosing different groups of VDTs are provided in Table 6. A one-year increase in the age of the farmer is predicted to decrease the probability of adoption of VRT by 0.013, 0.020, and 0.012 for farmers adopting plant-based, soil-based, and both soil- and plant-based VDTs, respectively. For farmers who adopted both soil- and plant-based VDT, one more year of formal education is predicted to result in a 0.052 increase in the probability of adoption of VRT. Farmers using computers for farming operations are predicted to have 0.598, 0.563, and 0.418 higher probability of adoption of VRT when they adopt plant-based, soil-based, and both soil- and plant-based VDT respectively. The probability of adoption of VRT is lower by 1.586 for Texas cotton farmers who adopted soil-based VDT, and by 1.311 for those who adopted both soil- and plant-based VDT.

Table 6. Average marginal impact of variables on adoption of VRT

VDT	VRT	Variable	Average Marginal Impact		
			No weights	**Proportional weights**	**Raking weights**
Both	*yes*	*age*	-0.012	-0.012	-0.010
		edu	0.052	0.041	0.039
		comp	0.418	0.542	0.394
		texas	-1.311	-1.207	-1.037
	no			Base	
Soil	*yes*	*age*	-0.020	-0.016	-0.013
		edu	0.033	0.004	0.004
		comp	0.563	0.827	0.670
		texas	-1.586	-1.391	-1.379
	no			Base	
Plant	*yes*	*age*	-0.013	-0.014	-0.008
		edu	0.031	0.047	0.021
		comp	0.598	0.517	0.416
		texas	-0.536	-0.633	-0.333
	no			Base	

Conclusions

Technological breakthrough is a major driver of economic growth and competitiveness. Since any technology is of value only if it is put into practice by the end user, technology adoption is as important as technology development. Once prospective users are convinced about the advantages of the new technology—such as the ease, speed, economy, and efficiency of performing a task—they will adopt the technology after acquiring the necessary skills to use the technology or to modify the technology itself.

The adoption patterns, therefore, depend on factors such as awareness of the technology, existing skill set and machinery, exposure to the technology, adoption by peers, risk associated with changing to a new technology, and characteristics of the end user and the technologies. Understanding technology adoption patterns provides invaluable insights into the type of technologies most likely to be adopted and characteristics of the decision makers who are most likely to adopt new technologies. Understanding the mechanism of adoption helps to streamline Extension activities by enabling more informed decision-making on technology development, upgrading, and marketing.

PA is an important new technology that enhances input efficiency and reduces potential negative environmental impacts of agricultural chemicals by adjusting input applications to the crop requirements under temporal and spatial dimensions. Detection of the existence and extent of variability in the field with VDT and application of inputs at variable rates to match the variability by using VRT are two main aspects of PA. This study examined the adoption of both VDT and VRT, and analyzed the inter-relationship between their adoption patterns.

The results revealed that the most widely adopted type of VDT is the soil-based one, primarily due to its relatively lower cost and fewer required technical skills. Another interesting finding is the prevalence of partial adoption of PA technology, which is evident from the fact that most of the surveyed farmers chose not to adopt VRT even after adopting some type of VDT. The partial adoption decision by farmers may be due to the fact that some farmers who adopted VDT did not find enough variability within their field to justify the adoption of VRT. Further, it was found that the farmers who have adopted both soil- and plant-based VDTs were most likely to adopt VRT. The higher rate of joint adoption of both soil- and plant-based VDTs and VRT indicates that PA adopters tend to use site-specific information on both soil fertility and plant growth to decide on variable rate input applications. The significance of such information is further supported by the fact that acquiring variability data using both soil- and plant-based VDT leads to a higher adoption rate of VRT.

Farm size, exposure to Extension activities, and percentage of land owned by a farmer were found to have significant impacts on the choice of the VDT. The age-education complex appears to have a significant impact on the adoption of VRT. In particular, younger and more educated farmers were more likely to adopt VRT. Cotton farmers in Texas were found to be less likely to adopt VRT compared to farmers in the other surveyed, southern states of the United States. This finding is consistent with the low within-field variability in the cotton-producing regions of Texas, which are largely located in the northern plains, and with the presence of a large number of dryland farms therein that are not intensively managed.

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