Adoption of Variability Detection and Variable Rate Application Technologies by Cotton Farmers in Southern United States

Shyam Nair
Chenggang Wang
Eduardo Segarra
Eric Belasco
Department of Agricultural and Applied Economics
Texas Tech University

Margarita Velandia
Department of Agricultural and Resource Economics
University of Tennessee

Jeanne Reeves
Cotton Incorporated
Cary, NC.

Selected Paper prepared for presentation at the Agricultural & Applied Economics Association's 2011 AAEA & NAREA Joint Annual Meeting, Pittsburgh, Pennsylvania, July 24-26, 2011

Adoption of Variability Detection and Variable Rate Application Technologies by Cotton Farmers in Southern United States

Abstract

A nested logit model was used to analyze the 2009 Southern Cotton Precision Farming Survey to study the impact of farmer and farm characteristics on the adoption of Variability Detection Technologies (VDT) and the adoption of Variability Rate application Technology (VRT) conditioned on the type of the VDT chosen. The results showed that the farm size and exposure to extension activities are important factors affecting the choice of VDTs. The farmers adopting both soil and plant based VDTs are more likely to adopt VRT. The probability of adoption of VRTs was lower for Texas cotton farmers irrespective of the type of VDT adopted. In general, younger, more educated farmers who use computers for farming operations are more likely to adopt VRT when they choose soil based or both soil and plant based VDT.

Key words: Precision Agriculture, Technology Adoption, Cotton

JEL Classification: O33; Q16

Adoption of Variability Detection and Variable Rate Application Technologies by Cotton Farmers in Southern United States

Precision Agriculture (PA) is a management practice that aims at sustainable crop production by matching resource application and agronomic practices to the spatial and temporal variability in field conditions and crop requirements (Whelan and McBratney, 2000). PA not only increases resource use efficiency but also reduces the negative environmental impact of harmful agricultural chemicals (Pierce and Nowark, 1990). Even with these potential advantages, and despite US being a major producer and leading exporter of cotton, the adoption rate of PA practices is low among US cotton farmers. The low adoption rate is usually attributed to farmers' lack of awareness of the existing precision agriculture technologies in the market (Daberkow and McBride, 2000), high technology costs, and difficulty in proper understanding of the technology and interpretation of the data (Reichardt and Jurgens, 2009).

The main components of PA are collection and processing of field variability data, and variable rate application of inputs (Blackmore *et al.*, 2003). The data collection and processing techniques are used to quantify the variability in fertility or crop growth within a field and we call these variability detection technologies (VDTs). Examples of VDTs are zone soil sampling, grid soil sampling, electrical conductivity, yield monitors, aircraft imagery and satellite imagery. Once the field variability data are collected, the field is delineated into homogeneous management zones according to the variability in the field for which a single rate of a specific crop input is appropriate (Doerge, 1998). The application of inputs to these zones at different rates matching the field variability is known as Variable Rate Technology (VRT).

Although the adoption of individual VDTs and VRTs has been extensively studied (Daberkow and McBride, 2003; McBride and Daberkow, 2003; Larson et al., 2008; Walton et al., 2008; Walton et al., 2010), little is known of 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; Roberts *et al.*, 2004) considered a single VDT and tried to analyze the relationship between adoption of that technology and adoption of VRT and did not address the question of how the adoption of a specific VDT or group of VDTs affect the adoption of VRT. The use of VDTs to detect the variability in the field may or may not increase the likelihood of adopting VRTs, depending on the revealed extent and distribution of field variability. On the one hand, field variability seems essential information for the decision to adopt VRTs. On the other hand, field variability data may allow farmers to remove the excessive details within individual management zones, resulting in simplified management zoning and reduced need for VRT equipments (Zhang *et al.*, 2002). For example, in Brazil the adoption rate of VRT is very low despite the high adoption rate of yield monitors (Lowenberg-DeBoer, 1999). Hence estimating the probability of a decision maker choosing to adopt a particular VDT from different available technologies, and estimating the adoption of VRT conditioned on chosen VDT will provide a better understanding of the adoption behavior. Moreover, there is a need to compare the adoption pattern of Texas, which is the number one cotton producing state in the US, with other cotton growing southern US states.

Understanding the adoption patterns of various precision agriculture technologies will be useful to researchers, extension agents, and agro-industry. It provides insights into the farm and farmer characteristics that influence the diffusion of these technologies, as well as the type of technologies most likely to be adopted by specific farm and farmer groups. 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 discussed earlier, the adoption of VRT may depend on the type of the VDT chosen by the decision maker. The nested logit model enables one to analyze the impact of independent variables on the choice of an alternative from a discrete, mutually exclusive, and exhaustive choice sets at different levels of decision making. Hence a Random Utility Model (RUM) consistent nested logit model serves as the ideal tool to study the factors influencing the choice of a specific group of VDTs from the available choice set and those affecting the adoption of VRT for farmers adopting each group of VDT.

We consider a nested logit model of two levels. The first level models the farmers' choice over a set of VDTs. The second level models the decision on adoption of VRT for each group of VDT adopted. The conceptual framework of the nested logit model is described below (Mc Fadden 1974; 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 random utility model, let $U_{tj} = V_{tj} + \varepsilon_{tj}$, where $k \in R_j$. Then the error term ε_{tj} is distributed as a Gumbel distribution of the form

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

where ρ_t is the scale parameter (Cameron and Trivedi, 2005), which is a function of the correlation between ε_{tj} and ε_{tk} , and $\rho_t = \sqrt{1 - Corr\left[\varepsilon_{tj}, \varepsilon_{tk}\right]}$

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 given below.

$$V_{tj} = A_t\alpha_t + B_{tj}\beta_j \tag{2}$$

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

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

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

where J_t is called the inclusive values or log-sums for first level given by the following equation:

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

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

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

$$+B_{itj}\beta_j|\rho_t - \log\sum_{j\epsilon S_t}\exp B_{itj}\beta_{jk}|\rho_t \tag{6}$$

Data and Empirical Strategy

The data for this study was from the 2009 Cotton Inc. Southern Precision Farming Survey (Mooney et al., 2010). The survey received 1981 responses from cotton farmers of 12 southern US states (Alabama, Arkansas, Florida, Georgia, Louisiana, Missouri, Mississippi, North Carolina, South Carolina, Tennessee, Texas, and Virginia). Apart from questions related to the status of adopting precision agriculture practices, the survey respondents provided information about themselves, the characteristics of their farm and farming operations. This is the first time that the survey included Texas, the largest cotton producing state in the US, and the large number of responses from Texas permits comparison of the adoption pattern between Texas and other southern 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 is the adoption of only soil based VDT such as grid soil sampling, zone soil sampling, use of electrical conductivity maps and use of soil survey maps. The second group is the adoption of only plant based VDT such as yield monitor, aircraft imagery, and satellite imagery. The third group is the adopters of both soil and plant based VDT. The fourth group has adopted none of these VDTs. These four groups are designated as *soil*, *plant*, *both*, and *none* respectively in the nested logit model. The farmers adopting any VRT were considered as adaptors of VRT and were designated as y in the nested logit model.

After rearranging the respondents from the survey into four groups of VDT adopters and two groups of VRT adopters, 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 is presented in Figure 1.

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 choice set with the description of choices is provided in Table 1.

The survey responses provided information on the farm and farmer characteristics. This information, together with the farm's location, provided the data on the independent variables that may influence the adoption of VDT, VRT or both. The regressor variables used in the study were the age of farmer, farming experience, level of education, familiarity with computers, income, exposure to extension publications, farm size, percentage of the farm irrigated, percentage of the farm owned, and productivity. Location of the farm was used as a dummy variable to distinguish the farms located in Texas from those in other surveyed states. All the explanatory variables used in the study and their detailed description are provided in Table 2.

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

A large number of candidate models that make theoretical sense with different combinations of the available explanatory variables were estimated to select the model with the best fit. Among the models that converged, the best one was selected using the Likelihood Ratio (LR) test where $LR = -2(LL_R - LL_{UR})$ when models with different number of variables were compared and by choosing the models with maximum log likelihood when models with the same number of variables were compared. The final model selected has six variables, two of which (area and ext) influence the choice of VDTs and the remaining four (age, edu, comp, and texas) influence the adoption of VRT for each of these groups.

Missing values in some explanatory variables resulted in removal of about 26% percentage of the total of 1981 observations. Together with the low response rate of the survey, this suggests the sample may not be representative of the population. Post stratification weights based on the 2002 agricultural census were used to tide over this problem. The observations were grouped into 72 classes corresponding to the 12 states and 6 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, 1000-1999, and 2000 or more. After grouping the observations to these strata, the weights were estimated using two methods. 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 (Lambert, 2010).

Results and Discussion

The frequency analysis of the adoption percentages in the data showed that 2.87% of the farmers adopted plant based VDT only, 21.71% adopted soil based VDT only and 7.37% adopted both soil and plant based VDT. The average predicted probabilities for adoption of plant based, soil based and both plant and soil based VDTs were 0.0291, 0.2171, and 0.0741 respectively, which are close to the actual values indicated by the data demonstrating a good fit of the model. Among the farmers who adopted both soil and plant based VDT, 67.59% adopted VRT whereas the adoption percentage of VRT were 35.85% and 28.67% respectively for farmers adopting soil based and plant based VDT.

Adoption of VDTs

The coefficient estimates for the variables hypothesized to influence the adoption of VDTs are provided in Table 3. As expected, the farm size had a positive and significant impact on the adoption of plant based VDT. Cotton yield monitor is the major plant based VDT and the positive effect of the farm size on the adoption of yield monitors has been reported by several researchers (Just *et al*., 1980; Daberkow and McBride, 2003; Reichardt and Jurgens, 2009). Yield monitor is a capital intensive technology and hence can be efficiently adopted by farmers operating larger farms only. The non-divisibility of the technology is likely to discourage adoption by decision makers having farm sizes below a critical limit as adoption requires equipments that may be profitable to use only in larger farms (Just *et al.,* 1980). Moreover, the other two VDTs grouped as plant based VDT (aircraft imagery and satellite imagery) are also more appealing 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 economy of scale is very important.

The farm size does not significantly influence the adoption of soil based VDT when the data was analyzed with and without the post stratification weights. The major VDTs included in this group are grid soil sampling, zone soil sampling and electrical conductivity. The adoption of these VDTs may not depend on the size of the farm as the number of soil samples taken increases with 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 may be the inclusion of Texas data in our study which has a significant number of less intensively managed large cotton farms and low within-field variability. The adoption of both soil and plant based VDT was positively and significantly influenced by the farm size.

The exposure of farmers to university extension activities had a positive bearing 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 ($p > |z| = 0.09$), the analysis with both proportional weights and weights derived using raking procedure showed a significant effect for farmers adopting plant based VDT also. The soil based VDTs are not as costly as the plant based VDTs and are not much influenced by the farm size. This may be the reason for extension activities to significantly influence the adoption of soil based VDT, but have no major impact on the adoption of plant based VDTs. The impact of exposure to university extension activities on the frequency distribution of the adoption probability of soil based and both soil and plant based VDTs are illustrated in Figure 2 and Figure 3, respectively. The adoption probability distribution of farmers who have been exposed to university extension activities is relatively skewed towards the right compared to those who have not.

The estimated average marginal impacts of the variables on the probability of different groups of the VDT are provided in Table 4.This results show that the average marginal impact of the farm size on the adoption of all groups of VDTs are 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 0.00044. The probabilities of adoption of soil based VDT, plant based VDT, and both soil and plant based VDT are respectively 0.1078, 0.0177, and 0.0341 higher for the farmers utilizing university extension activities.

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 effect on the adoption of VRT for farmers choosing soil based VDT and both soil and plant based VDT. The effect of age of the farmer on the adoption of VRT for farmers adopting only plant based VDT is also significant at 10% alpha level, a result found by several other researchers (Daberkow and McBride, 2000; Daberkow and McBride, 2003; Larson *et al.*, 2008; Walton *et al.*, 2010). The higher level of new technologies adoption by younger farmers can be attributed to the availability of larger planning horizon that leads to lower level of risk aversion for younger farmers. Moreover younger farmers generally have less experience and familiarity with the existing technologies and hence are less reluctant to change existing practices.

The education of the decision maker is another factor that significantly influences 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; 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 level also indicates possibility of having better learning skills and so will help the farmers to learn new practices with ease.

Even though the use of computers for farming operations significantly influenced the adoption of VRT for farmers adopting only soil based VDT at 5% alpha level, computer use for farming operations have 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 for the farming operations was found to be a significant determinant of the adoption of PA by several researchers (Daberkow and McBride 2003; 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 for the use of these VDTs 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. The possible reason for lower adoption of VRT in Texas may be the lower inherent within-field variability in Texas plains, which accounts for most of the cotton acreage and production in Texas and the presence of a large number of dryland cotton farms in Texas that are less intensively managed. The variation in the adoption rate of PA among geographical locations was reported by several researchers (Lowenberg-DeBoer 1999; Daberkow and McBride 2000; Walton *et al*. 2010). Figure 2.6 shows a shift in probability of adoption towards the left side for the cotton farmers in Texas indicating the lower adoption levels in Texas compared to the other surveyed southern states.

The estimated average marginal impacts of the variables on the probability of adoption of VRT for farmers choosing different groups of VDTs different groups of the VT are provided in Table 6. One year increase in the age of the farmer is predicted to decrease the probability of adoption of VRT by 0.014, 0.023, and 0.013 for farmers adopting plant based, soil based and both soil and plant based VDTs respectively. For the farmers who adopted both soil and plant based VDT one more year of formal education is predicted to result in a 0.056 increase in the adoption probability of VRT. Farmers using computers for farming operations are predicted to have 0.60, 0.66, and 0.45 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 1.84 for Texas cotton farmers who adopted soil based VDT and by 1.37 for those who adopted both soil and plant based VDT.

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 the prospective user is convinced about the advantages of the new technology, such as the ease, speed, economy, and efficiency of performing a task, she will adopt the technology after acquiring the necessary skills to use the technology or modifying the technology itself.

The adoption patterns, therefore, depend on such factors as awareness about 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 more probable to adopt new technologies. Understanding the mechanism of adoption helps to streamline the 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 negative environmental impacts of the agricultural chemicals by adjusting input application to the crop requirement in temporal and spatial dimensions. Detection of the existence and extent of variability in the field with VDT and variable application of inputs to match the variability by using VRT are two main aspects of PA. This study has examined the adoption both VDT and VRT and analyzed the inter-relationship between their adoption patterns.

The results revealed that the most widely adopted VDT is the soil based one, primarily due to its relatively lower cost and fewer required technical skills. Further, the farmers who have adopted both soil and plant based VDT are most likely to adopt VRT. The higher rate of joint adoption of soil and plant based VDT indicates that the PA adopters tend to use site-specific information of both soil fertility and plant growth. The significance of such information is further supported by the fact that acquiring it leads to a higher adoption rate of VRT.

The farm size and exposure to extension activities were found to have a significant impact 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 are more likely to adopt VRT. The cotton farmers in Texas were found to be less likely to adopt VRT compared to farmers in the other surveyed southern US states. This finding is consistent with the low within-field variability in the cotton producing regions of Texas, which are largely plains, and with the presence of a large number of dryland farms therein that are not intensively managed. Therefore, service providers and extension agents should not concentrate their resources in areas like Texas Great Plains with low inherent spatial variability.

References

Akridge, J.T., and L.D. Whipker. 1999. “Precision agricultural services and enhanced seed dealership survey results, 1999”. Center for agricultural business, Purdue University. Staff paper No. 99:6.

Batte, M., and R. Johnson. 1993. “Technology and its impact on American agriculture”. In: Size structure and the changing face of American agriculture, ed (Hallum,A.). Westview Press Inc., CO. USA.

Blackmore, S., R. Godwin, and S. Fountas. 2003. “The analysis of special and temporal trends in yield map data over six years”. Biosystems Engineering. 84(4): 455-466.

Brackstone, G.J., and J. N. K. Rao. 1976. “Survey Methodology: Raking Ratio Estimators”. A Journal Produced by Statistical Services , Statistics Canada. 2(1): pp. 63-69.

Cameron, A.C., and P.K. Trivedi. 2005. “Microeconometrics: Methods and Applications”. Cambridge University Press.

Daberkow, S.G. and W.D. McBride. 2000. “Adoption of precision agriculture technologies by U.S. farmers”. 5th international conference on precision agriculture, Bloomington, Minnesota, USA.

Daberkow, S.G. and W.D. McBride. 2003. “Farm and operator characteristics affecting the awareness and adoption of precision agriculture technology”. Precision Agriculture. 4: 163-177.

Doerge, T. 1998. “Defining management zones for precision farming”. Crop Insights 8(21). Pioneer Hi-Bred International Inc. Iowa.USA.

Just, R., D. Zilberman, and G. Rausser. 1980. “A putty-clay approach to the distributional effect of new technologies under risk”. In: Operations research in agriculture and water resources. Eds (Yaron, D., and Tapiero, C). North Holland Publishing Company, NY.USA.

Khanna, M. 2001. “Sequential adoption of site specific technologies and its implications for nitrogen productivity: A double selectivity model”. American journal of agricultural economics. 83: 35-51.

Lambert, D. 2010. ”Post-stratification Survey Weights for the Cotton Inc. 2009 Cotton Producer Survey on Precision Agriculture”. Unpublished Document.

Larson, J.A., R.K. Chambers, B.C. English, S.L. Larkin, M.C. Marra, S. W. Martin, K.W. Paxton, and J.M. Reeves. 2008. “Factors affecting farmer adoption of remotely sensed imagery for precision management in cotton production”. Precision Agriculture. 9: 195-208.

Lowenberg-DeBoer, J. 1999. “Precision agriculture in Argentina”. Modern Agriculture. 2(2):13-15.

McBride, W.S., and S.G. Daberkow. 2003. “Information and the adoption of precision farming technologies”. Journal of Agribusiness. 21(1): 21-38.

McFadden, D. 1974. “The measurement of urban travel demand”. Journal of Public Economics. 3:303-328.

Mooney, D.F., R. K. Roberts, B. C. English, J. A. Larson, D. M. Lambert, M. Velandia, S. L. Larkin, M. C. Marra, R. Rejesus, S. W. Martin, K. W. Paxton, A. Mishra, E. Segarra, C. Wang, and J. M. Reeves. 2010. Proceedings of the 2010 Beltwide Cotton Conference, New Orleans, Louisiana, January 4-7, 2010.

Pierce, F., and P. Nowak.1999. “Aspects of precision agriculture”. Advances in Agronomy, Volume 67.

Reichardt, M., and C. Jurgens. 2009. “Adoption and future perspective of precision farming in Germany: results of several surveys among different agricultural target groups”. Precision Agriculture. 10: 73-94.

Roberts, R.K., B.C. English, J.A. Larson, R.L. Cochran, S.L. Larkin., et.al. 2004. “Adoption of site-specific information and variable rate technologies in cotton precision farming”. Journal of Agricultural and Applied Economics. 36:143-158.

Sevier, B. J., and W. S. Lee. 2004. “Precision agriculture in citrus : A probit model analysis for technology adoption”. ASAE paper no. 041092, American society of agricultural engineers.

Train, K. 2003. “Discrete Choice Methods with Simulation”. Cambridge University Press.

Walton, J.C., D.M. Lambert, R.K. Roberts, J.A. Larson, B.C. English, S.L. Larkin, S.W. Martin, M.C. Marra, K.W. Paxton, and J.M. Reeves. 2008. “Adoption and Abandonment of Precision Soil Sampling in cotton production”. Precision Agriculture. 11:135-147.

Walton, J.C., R.K. Roberts, D.M. Lambert, J.A. Larson, B.C. English, S.L. Larkin, S.W. Martin, M.C. Marra, K.W. Paxton, and J.M. Reeves. 2010. “Grid soil sampling adoption and abandonment in cotton production”. Precision Agriculture. 11:135-147.

Whelan, B.M., and A.B. McBratney. 2000. “The null hypothesis of precision agriculture management”. Precision Agriculture. 2: 265-279.

Zhang, N., M. Wang, and N. Wang. 2002. “Precision agriculture-a worldwide overview”. Computers and Electronics in Agriculture. 36: 113-132.

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

No.	Choice	Description
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

Table 2. The description of the explanatory variables analyzed

Variable Name	Description
age	Age of the decision maker in years
exp	Farming experience 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
inc1	Dummy variable that assumes the value of 1 if the annual household income is less than $99,000 and 0 other wise
inc2	Dummy variable that assumes the value of 1 if the annual household income is between $100,000 and 199,999 and 0 other wise
inc3	Dummy variable that assumes the value of 1 if the annual household income is greater than $200,000 and 0 other wise
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
peririg	Percentage of the area cultivated that is irrigated
perown	Percentage of the area cultivated that is owned by the decision maker
prod	Average productivity of the farm
yr	The difference between the productivity of the highest yielding one third of the farm and the lowest yielding one third of the farm.
texas	Dummy variable that assumes the value of 1 if the farm is located in Texas and 0 otherwise

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	0.0007	0.0001	<0.001	0.0008	0.0001	<0.001	0.0009	0.0001	<0.001
	ext	0.8418	0.2693	0.002	0.8535	0.2742	0.002	0.8450	0.2673	0.002
soil	area	0.0001	0.0001	0.161	0.0001	0.0001	0.254	0.0002	0.0001	0.148
	ext	0.6850	0.1488	<0.001	0.8127	0.1748	<0.001	0.7780	0.1702	<0.001
plant	area	0.0004	0.0002	0.021	0.0004	0.0002	0.050	0.0004	0.0002	0.067
	ext	0.5848	0.3447	0.090	0.9861	0.410	0.016	0.7742	0.3893	0.047
None						Base				
LL / log pseudolikelihood		-1695.199			-16922.448			-16918.847		
Wald χ^2		465.760			439.500			511.490		
$p > \chi^2$		<0.001			<0.001			<0.001		

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

VDT	Variable	Average Marginal Impact		
		No weights	Proportional weight	Raking weights
Both	area	4.40×10^{-6}	2.97×10^{-6}	4.80×10^{-6}
	ext	0.0341	0.0444	0.0435
Soil	area	NS	NS	NS
	ext	0.1078	0.1488	0.1433
plant	area	9.62×10^{-6}	1.11×10^{-5}	1.06×10^{-5}
	ext	0.0177	0.0280	0.0209
none			Base	

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	-0.086	0.040	0.029	-0.090	0.045	0.048	-0.075	0.039	0.052
		edu	0.378	0.157	0.016	0.291	0.136	0.032	0.285	0.124	0.022
		comp	3.024	1.594	0.058	3.881	2.584	0.133	2.939	2.296	0.201
		texas	-9.273	3.533	0.009	-8.506	4.306	0.048	-7.529	4.160	0.070
	no					Base					
soil	yes	age	-0.145	0.055	0.009	-0.121	0.073	0.094	-0.101	0.061	0.103
		edu	0.240	0.150	0.110	0.027	0.152	0.859	0.029	0.145	0.846
		comp	4.146	1.557	0.008	6.091	2.591	0.019	4.898	2.157	0.023
		texas	-11.62	3.565	0.001	-10.01	3.520	0.004	-9.951	3.776	0.008
	no					Base					
plant	yes	age	-0.082	0.047	0.078	-0.076	0.050	0.134	-0.048	0.044	0.275
		edu	0.209	0.182	0.253	0.262	0.254	0.301	0.134	0.179	0.453
		comp	3.524	1.968	0.073	2.812	2.422	0.246	2.569	2.423	0.289
		texas	-3.472	2.119	0.101	-3.632	3.534	0.304	-2.220	3.037	0.465
	no					Base					

Table 6. Average marginal impact of variables on adoption of VRT at each group of VDT

VDT	VRT	Variable	Average Marginal Impact		
			No weights	Weights (proportional)	Weights (raking)
Both	yes	age	-0.0128	-0.1331	-0.0112
		edu	0.0559	0.0433	0.0423
		comp	0.4468	0.5773	0.4361
		texas	-1.3702	-1.2654	-1.1174
	no			Base	
Soil	yes	age	-0.0228	-0.0187	-0.0159
		edu	NS	NS	NS
		comp	0.6553	0.9395	0.7746
		texas	-1.8360	-1.5441	-1.5738
	no			Base	
Plant	yes	age	-0.0140	-0.0138	-0.0084
		edu	NS	NS	NS
		comp	0.6012	0.5134	0.4468
		texas	NS	NS	NS
	no			Base	

Figure 1. Description of the tree structure of the nested logit model

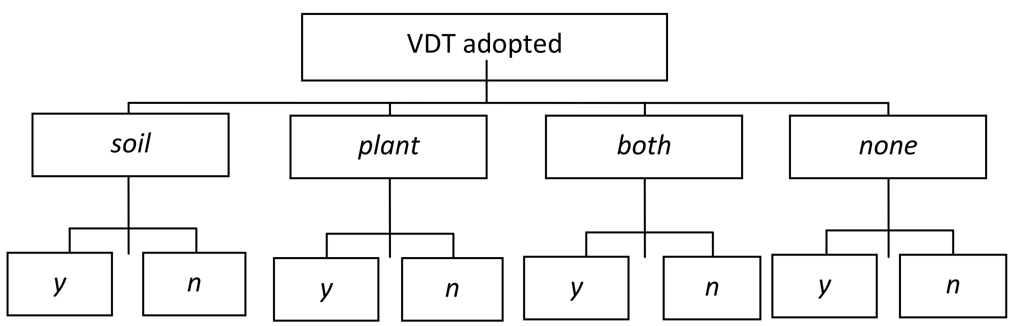

Figure 2. Impact of exposure to university extension activities on the Frequency distribution of the probability of adoption of both soil and plant based VDT.

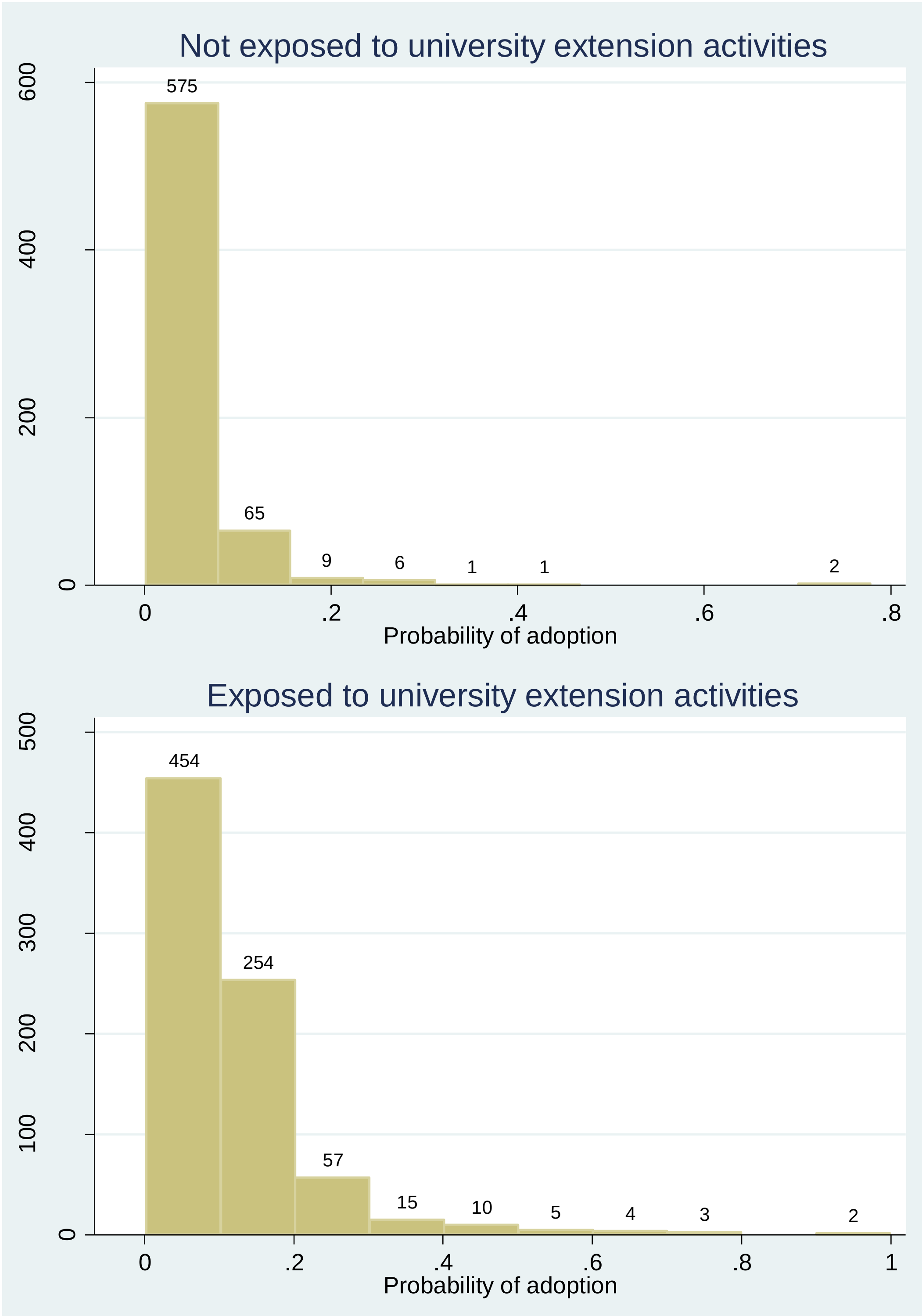

Figure 3. Impact of exposure to university extension activities on the Frequency distribution of the probability of adoption of soil based VDT.

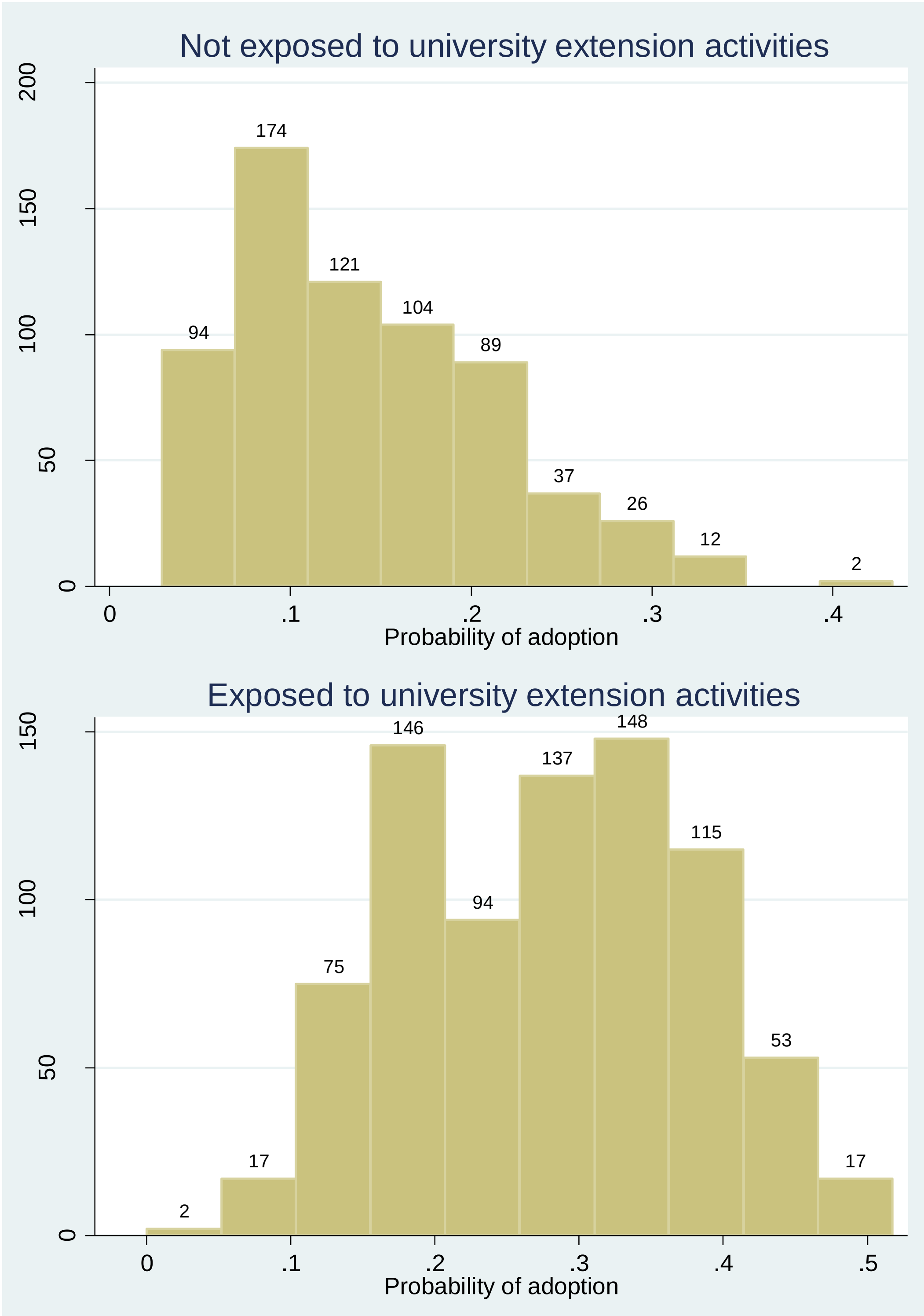

Figure 4. Impact of location of the farm on the Frequency distribution of the probability of adoption of VRT for farmers adopting both soil and plant based VDT.

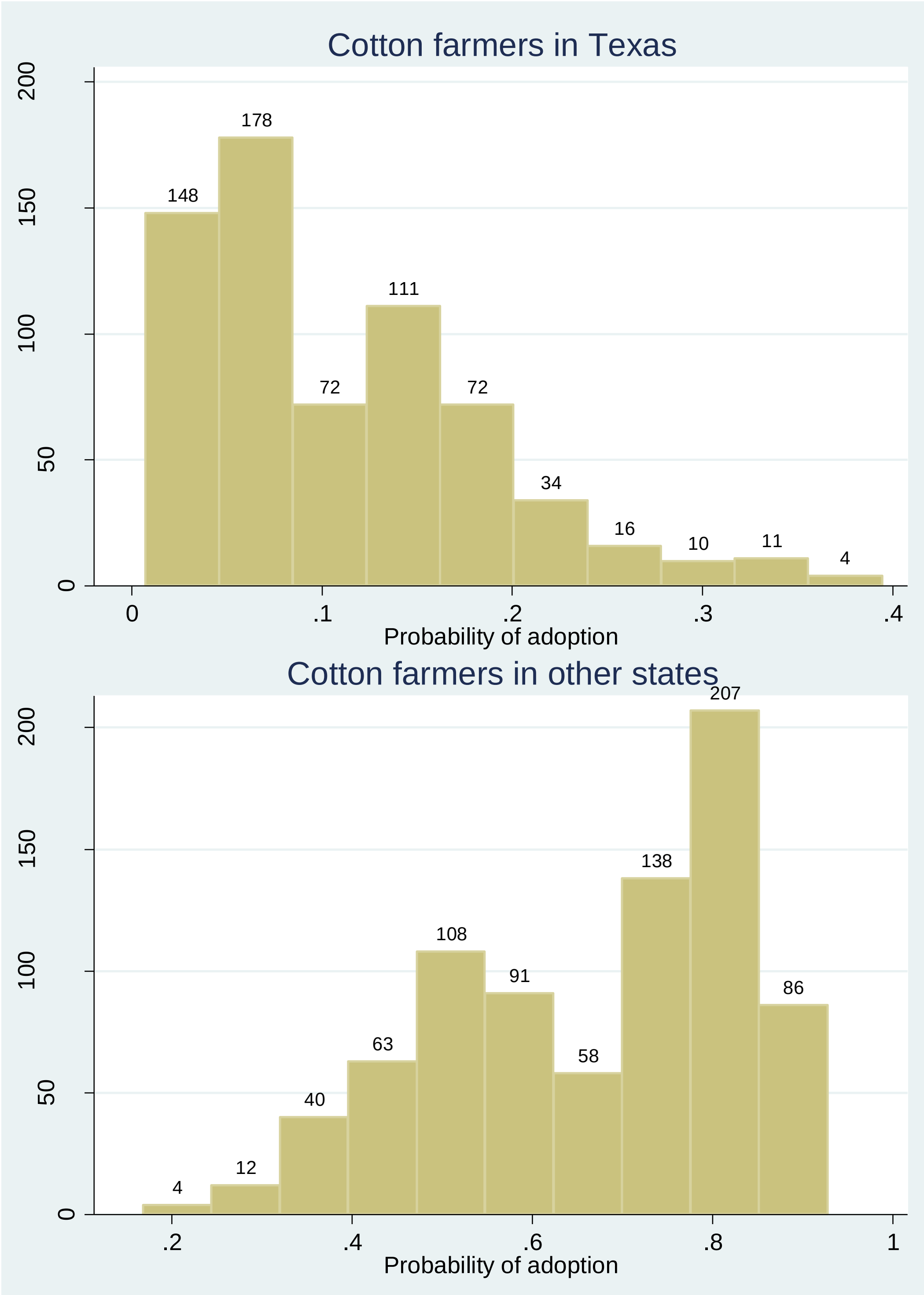

Figure 5. Impact of location of the farm on the Frequency distribution of the probability of adoption of VRT for farmers adopting soil based VDT.