Factors Influencing Adoption of Remotely Sensed Imagery for Site-Specific Management in Cotton Production

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Abstract: This research evaluated the factors that influenced cotton producers to adopt remote sensing for variable rate application of inputs. Farmers who were younger, more highly educated, had a larger farm operation, and were more technologically savvy were more likely to have adopted remote sensing.

Keywords: Aerial imagery, precision farming, satellite imagery, variable rate technology.

JEL Classifications: D21, Q12, Q16.

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Introduction

Site-specific management (also known as precision farming or precision agriculture) is the application of spatial management technologies to the monitoring and control of crop production (National Research Council). The suite of technologies includes electronic applications such as global positioning systems (GPS), yield monitors, geographic information systems (GIS), and variable rate technologies (VRT) that use controllers on application equipment to vary input amounts across a farm field. Farmers can use these technologies to exploit information about spatial variability in farm field characteristics to improve profitability by varying inputs to meet crop needs in different areas of the field.

One site-specific management technology that is showing considerable potential in agriculture is aerial or satellite (remotely sensed) imagery (Lowenberg-DeBoer, Pinter, Jr. et al.). Our study evaluated the factors that influenced the adoption decision for cotton farmers using remotely sensed imagery for variable rate application of inputs. The sunlight reflected off the surfaces of crops and soils can be measured using aerial or satellite imagery and used to identify different characteristics of the vegetation or soil. The reflectance data obtained with remotely sensed imagery can be used in crop management when it is related to a measure of the growing plant canopy such as leaf area index or percent ground cover (Barnes et al., Hong et al.). One commonly used vegetative index is the normalized difference vegetation index (NDVI). Thus, remote sensing can be used to obtain spatially distributed reflectance data on plant growth development at different stages of the growing season (Maas, Plant et al., Zarco-Tejada, Ustin, and Whiting). Remotely sensed imagery of bare soil also can be used to identify soil characteristics in farm fields (Dalal and Henry, Shonk et al., Leone et al.). Potential uses of remotely sensed imagery in site-specific management include management of nutrients, water, and pests (Barnes et al., Pinter, Jr., et al., Tenkorang and Lowenberg-DeBoer). Remote sensing also has been used to predict crop yields (Doraiswamy et al.) and farm income (Nivins, Kastens, and Dhuyvetter), to facilitate compliance monitoring with government and crop insurance program provisions (Hall), to identify management zones in fields (Larson et al., Overstreet et al.), and to apply plant growth regulators and harvest aids in cotton production (Pinter Jr. et al.).

The ability to do in-season monitoring and control is particularly important in cotton production. Cotton farmers often time the application of inputs such as irrigation water, plant growth regulators, pesticides, and harvest aids based on the stage of plant growth and development (Bourland Oosterhuis, and Tugwell). The use of crop consultants that provide knowledge-based field scouting and input recommendation services during the growing season is important in cotton production. For example, Edens et al. reported that 46% of Tennessee cotton farmers used crop consultants. Thus, remote sensing may have great potential in cotton production because imagery can be obtained at regular intervals during the growing season and can be related to current crop status.

Cotton farmer interest in remote sensing has been growing with the introduction of new remote sensing services targeting in-season management of the crop. For example, InTime, Inc. started offering aerial remote sensing services specifically for cotton in 2003. InTime, Inc. reported that 65,000 acres of cotton were remotely sensed in the mid-south region of the United States in 2003 (GoinTime.com). They estimated that about 250,000 acres of cotton were remotely sensed using their service in 2004 (Gointime.com). The company currently offers its services in 12 states and has expanded to include other crops such as peanuts, rice, orchard crops, and vegetables. InTime, Inc. provides digitally processed maps at the field level at frequent intervals during the growing season to subscribers via their internet web site. Subscribers also have the ability to make prescription maps for VRT application on the InTime web site. The farmer or the crop consultant can create and download the prescription maps for input into the VRT controller on the applicator. John Deere Agri Services in 2005 introduced an aerial imagery service similar to InTime to provide remotely sensed images, prescription maps, and other consulting services to cotton farmers (Brown and Wesch).

Numerous studies have analyzed the effects of farm and farmer characteristics on adoption of site-specific farm management technologies (e.g., Arnholt, Batte, and Prochaska, Batte and Arnholt, Daberkow, Fernandez-Cornejo, and Padgitt, Daberkow and McBride, Khanna, Khanna, Epouhe, and Hornbacker, Napier, Robinson, and Tucker, Norton and Swinton, Plant, Popp and Griffin, Roberts et al., (2002, 2004), Swinton and Lowenberg-DeBoer). However, information on the adoption of remotely sensed imagery by farmers is sparse. Results from the 1999 Agricultural Resource Management Survey (ARMS) survey by the U.S. Department of Agriculture indicated that farmers used remotely sensed imagery on 12.7% of U.S. corn area (Griffin et al.). By 2001, however, farmers used remote sensing on only 3.4% of U.S. corn area. Data from the ARMS survey indicated that the U.S. crop area on which remotely sensed imagery was used also was declining for soybeans and wheat. The factors that may have influenced the drop in the use of remotely sensed imagery in grain and oilseed production include a lack of perceived usefulness, a paucity of reliable analysis or consulting services, and the need to only purchase maps of bare soil once because the basic soil characteristics do not change over time (Griffin et al.).

While the ARMS survey provides data on crop acreage under remote sensing, it does not provide estimates on adoption for high value crops such as cotton, sugar beets, fruits, and vegetables. However, Roberts et al. (2002) in a summary of a 2001 mail survey of cotton producers in six southern U.S. states indicated that 2% of 1,373 survey respondents used aerial or satellite imagery. In addition, Lowenberg-DeBorer reported that satellite imagery was used to manage nitrogen on 100,000 acres of sugar beets in Minnesota and North Dakota in 2002. Daberlow, McBride, and Ali identified several farm decision maker and farm operation characteristics that influenced sugar beet growers in Minnesota and North Dakota to adopt remotely sensed imagery for nitrogen management. They found that operator age, farm size, percent of sugar beet acreage owned, use of computerized records, and having contracted production with the American Crystal Sugar Company positively influenced the adoption of remote sensing for nitrogen management. The American Crystal Sugar Company was supporting the use of remotely sensed imagery to manage nitrogen among its contract growers. Excess nitrogen reduces the harvestable sugar content in beets. Finally, Griffin et al. indicated that anecdotal reports suggest that remotely sensed imagery is being widely used in fruit, vegetable, and vineyard production.

Currently, some information exists on the adoption rates of remote sensing for some crops, but little information on adoption of specific remote sensing technologies, especially for specific high valued crops such as cotton. This study attempts to fill that void by focusing on remote sensing technology adoption for cotton. Our objective was to determine the farm and farmer characteristics that influence cotton producers to adopt remotely sensed imagery for VRT application of inputs.

Analytical Framework

The random utility model was used to analyze the adopt-not adopt decision for remote sensing technology (Ben-Akiva and Lerman, Louviere, Hensher, and Swait). Utility is an index that measures the relative satisfaction gained from different bundles of goods and services. The index embodies trade-offs among the different attributes of the choices being made by the decision maker. Utility is treated as a random variable in the model because the utility function of a farmer cannot be directly observed. Thus, the utility function for decision maker *n* is given by:

$$U_{yn} = V_{yn} + \varepsilon_{yn} = \beta`x_{yn} + \varepsilon_{yn}, \tag{1}$$

where U is the utility from adopting remote sensing technology, V_y is the deterministic portion of utility, ε is the random error term, β is a vector of parameters to be estimated, x is a vector of explanatory variables that are hypothesized to affect a farmer's decision to adopt remote sensing technology, and y is a discrete variable that equals 1 if the technology is adopted by farmer n and 0 if it is not adopted. A farmer would choose to adopt remote technology if $U_n(y = 1) > U_n(y = 0)$, that is,

$$V_n(y = 1) - V_n(y = 0) > \varepsilon_n(y = 1) - \varepsilon_n(y = 0), \tag{2}$$

for y=0, 1. Thus, the probability of an individual adopting remote sensing is given by:

$$\begin{aligned} P_n(y) &= Pr(U_n|y = 1 \geq U_n|y = 0) \\ &= Pr(V_n + \varepsilon_n \geq V_n + \varepsilon_n) \\ &= Pr(V_n - V_n > \varepsilon_n - \varepsilon_n). \end{aligned} \tag{3}$$

Assuming the random errors are independently and identically distributed across the not adopt-adopt alternatives ($y = 0, 1$) and N ($n = 1, \ldots$, N) decision makers as a Type I extreme value distribution, i.e., $\varepsilon_n = \varepsilon_n(y = 1) - \varepsilon_n(y = 0)$, Equation (3) has a standard logistic distribution that can be modeled using:

$$1 - F(-\beta' x_n) = \frac{\exp(\beta' x_n)}{1 + \exp(\beta' x_n)}. \tag{4}$$

A likelihood function can be defined in terms of the individual probabilities associated with each farmer's decision to adopt remote sensing as:

$$\ell(\beta_n \mid y_n, x_n) = \prod (1 - p(y = 1) \prod p(y = 0), \tag{5}$$

where y= 1 if the technology is adopted by farmer n and $y = 0$ if it is not adopted. The parameters are incorporated into the likelihood equation by using the relationship in Equation (3):

(6) $$\ell(\beta \mid y, x) = \prod F(-\beta' x \mid x, y=1) \prod [1 - F(-\beta' x \mid x, y=0)] .$$

Taking logs, the log likelihood equation is specified as:

(7) $$\ln \ell(\beta \mid y, x) = \sum \ln F(-\beta' x_{i} \mid x, y=1) + \sum \ln[1 - F(-\beta' x_{j} \mid x, y=0)] .$$

Coefficient estimates are found by maximizing the value of the log likelihood equation using the method of maximum likelihood. Once coefficient estimates are found, the probability that a specific farmer and/or farm would be observed to have adopted remote sensing technology can be predicted. The significance and magnitude of the parameter estimates also help to identify factors that may influence a farmer's decision to adopt remote sensing.

Data

A mail survey of cotton producers in Alabama, Arkansas, Florida, Georgia, Louisiana, Mississippi, Missouri, North Carolina, South Carolina, Tennessee, and Virginia was conducted in 2005 to ascertain information about their attitudes toward and use of precision farming technologies (Roberts et al., 2006). The U.S. Cotton Board provided a list of potential cotton producers for the 2003-2004 cotton marketing year (Skorupa). Following Dillman's general mail survey procedures, the questionnaire, a postage-paid return envelope, and a cover letter explaining the purpose of the survey were sent to each producer on January 28, 2005. A reminder post-card was sent one week later on February 4, 2005, and a follow-up mailing to non-respondents was sent three weeks later on February 23, 2005. The second mailing included a letter indicating the importance of the survey, the questionnaire, and a postage-paid return envelope. Of the 12,243 questionnaires mailed, 18 were returned undeliverable and 182 indicated they were not cotton farmers or had retired, leaving a total of 12,043 cotton producers. Of those cotton producers, 1,215 individuals provided data, giving a usable response rate of 10% (Roberts et al., 2006).

Data describing the characteristics of the farm decision maker and farm operation were collected from each survey respondent. Specifically, producers were asked to identify whether they used aerial photography or satellite imagery for each of eight VRT decisions. The alternative VRT input decisions were for fertility and lime, seed, plant growth regulators, harvest aids, fungicides, herbicides, insecticides, and irrigation. In addition, farmers were asked whether they used remote sensing for identifying management zones and mitigating drainage problems. Data on the use of other precision farm technologies and related services and sources of information also were collected from survey respondents. The data were used to specify the binomial logit model to analyze what farmer and farm characteristics influenced the decision to adopt. The number of usable responses was reduced from 1,215 down to 941 because of missing data for the logit model analysis (81 remote sensing adopters and 860 non-adopters).

Empirical Model

The dependent variable for the binomial logit model was use of aerial or satellite imagery for VRT decision making (*REMOTE*). The farm decision maker and farm operation characteristics utilized as explanatory variables in the logit model and their hypothesized signs are presented in Table 1.

The characteristics of the farm operation that were hypothesized to influence the decision to adopt remote sensing included farm size, household income, presence of irrigated production, and location. A larger farm size has been associated with increase adoption rates for precision technologies for some crops (Cowan, 2000). Also, a larger farm operation may be a proxy for the ability of a producer to bear the risk of adopting a new technology (Roberts et al., 2004). Farmers with larger farms and more fields may have more opportunities to observe spatial variability in farm fields (Larkin et al.). Remote sensing also may be a labor saving technology for larger farms by facilitating the identification of problem areas to be scouted rather than walking the whole field on the ground. Acres planted (*ACRE*) was the total acres planted in irrigated cotton, dryland cotton, and other crops in 2004 (1,000s acres). The proxy for farm size (*ACRE*) is expected to have a positive impact on the adoption of remote sensing.

A high income level could indicate the financial ability to make investments in site-specific technology and services (Larkin et al.). Thus, a positive sign is expected for the *INCOME* variable. The variable intended to capture the effects of high income (*INCOME*) was pre-tax household income for 2004.

Yields for irrigated cotton are generally higher than for dryland cotton and may be associated with higher input usage. Thus, more opportunities may exist for varying inputs with crop needs in different areas of farm fields under irrigation. In addition, remotely sensed imagery also can be used for non-VRT related crop decisions. For example, the reflectance data could be used to assess crop water status for the purpose of timing irrigations (Ritchie et al.). Irrigated cotton production has become much more common in the states covered by this survey and may be a factor in the adoption of remote sensing (USDA, NASS). The presence of irrigated cotton (*IRRIGATE*) was expected to positively impact the probability of adoption of remotely sensed imagery.

Location was modeled using a dummy variable (*LOCATION*) to test whether farmers in Alabama, Arkansas, Louisiana, Mississippi, Missouri, and Tennessee had a higher probability of remote sensing adoption relative to Florida, Georgia, North Carolina, South Carolina, and Virginia. The potential difference among these two regions is expected to be related to the availability of remote sensing and other precision technologies and services from agribusiness providers (Khanna). The mid-south states represented by *LOCATION* = 1 encompass the initial area where remote sensing services were offered by InTime, Inc. At the time of the survey, the base of InTime, Inc.'s remote sensing operation was Cleveland, MS, located south of Memphis, TN, with a branch office in Courtland, AL, located in northern Alabama south of Nashville, TN (Robinson, 2004).

The farm decision maker characteristics hypothesized to influence the remote sensing decision were age, education, computer use, and the individual who generated the map-based crop prescriptions for VRT application of inputs. A younger farmer may have a longer planning horizon, more exposure to new technologies, and may be more motivated to try new technologies compared to an older farmer (Roberts et al., 2004). These characteristics suggest that younger farmers are less risk averse (Dimara and Skuras), which would have a positive impact on farmers' perceptions of remote sensing technology. Thus, a farmer under age 40 (*AGE*) was expected to be more likely to adopt remote sensing technology than a farmer 40 years or more old.

Implementation of site-specific management on farm fields requires substantial analytical skills, which suggests that farmers with more years of formal education (*EDUCATION*) may be more likely to have the human capital needed to successfully evaluate and implement site-specific management (Roberts et al., 2004).

The use of computers is another important aspect of site-specific management (Arnholt, Batte, and Prochaska, Batte and Arnholt, Roberts et al., 2004). Farmers who use computers in farm management and more specifically, farmers who use computers in farm fields were expected to be more likely to adopt remote sensing than those who do not. An important element of successfully utilizing remotely sensed imagery for VRT decision making is the process of "ground truthing" the data to verify problems and identify treatment areas (Robinson, 2006). One method used for ground truthing is to scout the potential problem areas identified on the remotely sensed map and record the information into a portable computing devise. The question asking farmers whether they use a laptop or handheld computer in the field (*COMPUTER*) was used to capture this potential management characteristic of adopters. The use of computers in farm fields was expected to be positively associated with the adoption of remote sensing technology.

Another aspect of site-specific management is the analysis of spatial field data and the creation of prescription maps for VRT application. Who makes the maps could have an important influence on the decision to adopt remote sensing technology. A crop consultant or input dealer promoting precision services such as VRT map-making or VRT application may influence a farmer to purchase a subscription for remotely sensed imagery. In addition, the recent availability of user-friendly web-based tools for making prescription maps such as those offered by InTime, Inc., facilitate prescription map creation for independent consultants or farmers themselves. The explanatory variables for farmers who created their own map-based crop prescriptions (*SELF*), used a crop consultant to generate map-based crop prescriptions (*CONSULTANT*), or used an input dealer to generate map-based crop prescriptions (*DEALER*) were used to assess farmer preferences.

Perceptions of precision farming educational programs of the Extension Service and their impact on remote sensing adoption were captured using the *EXTENSION* variable. This variable represents the yes-no responses to a question asking farmers whether the Extension Service needs to provide more educational outreach about precision farming. Farmers who look to Extension as a source of information may be unwilling to invest in precision technology if they believe they have received insufficient information from Extension about potential costs and benefits. It was hypothesized that farmers who believed the Extension Service should provide more information were less likely to adopt remote sensing.

The unknown parameters were estimated using LIMDEP (Greene, 2002). Diagnostics for multicollinearity were performed (Belsley, Kuh, and Welsch). Marginal effects were calculated for each variable and represent changes in the variables on $Pr(y = 1)$(Greene, 2003). Marginal effects of the continuous variables were calculated by differentiating the probabilities with respect to the explanatory variables. Marginal effects of the dummy variables were computed as $Pr(y = 1|d = 1) - Pr(y = 1|d = 0)$, where d is the dummy variable.

Results and Discussion

The logit model estimated using 941 observations (81 remote sensing adopters and 860 non-adopters) is presented in Table 2. The likelihood ratio statistic of 121.2 was statistically significant at the 99% level (11 d.f.), which indicates that the model explained a significant proportion of the variance in the adoption of remote sensing by cotton farmers. The percentage of concordant and discordant pairs of observations with different responses in the model was 8.03% and 19.0%, respectively, with 0.7% ties. The concordant rate indicates an acceptable prediction rate. The model correctly predicted 92.4% of farmer's responses overall (83.3% for adopters and 92.8% for non-adopters).

The reliability of the test statistics used to determine significance of the coefficients in Table 2 could be questioned if the standard errors were seriously degraded by multicollinearity. Diagnostic tests for multicollinearity indicate potential problems with the intercept (*CONSTANT*) and farmer education (*EDUCATION*) variables. However, *CONSTANT* and *EDUCATION* were statistically significant at the 1% and 5% probability levels, respectively, indicating that the standard errors for the variables were not seriously degraded by multicollinearity (Belsley, Kuh, and Welsch).

The only independent variables that did not significantly explain the adoption of remote sensing were high household income, farmer use of a dealer to generate map-based crop prescriptions (*DEALER*), and farmer perceptions of the need for more precision farming educational programs by the Extension Service (*EXTENSION*). Even though about 70% of survey respondents believed that the Extension Service needed to provide more precision farming educational programs, this perception did not have a significant influence on the adoption decision.

All other variables describing the characteristics of farmers and their operations were statistically significant and had their hypothesized signs (Table 2). Farmers who were younger, more highly educated, or had larger farm operations were more likely to have used aerial or satellite imagery to make VRT management decisions on their farms. Marginal effects reported in Table 2 indicate that farmers under 40 years old were 3.5% more likely to use remote sensing, holding other variables at their means. For each additional year of formal education, the probability of a farmer adopting remote sensing increased by 0.7%, holding all other variables at their means. The probability of adoption rose by 0.9% for each 1,000-acre increase in crops planted in 2004.

Two other characteristics of the farm operation, the location of the farm and the presence of irrigated cotton, had positive impacts on the decision to adopt remote sensing technology. Holding other variables at their means, a farm located in Alabama, Arkansas, Louisiana, Mississippi, Missouri, or Tennessee was 3.1% more likely to have used remote sensing than a farm located in Florida, Georgia, North Carolina, South Carolina, and Virginia. Results indicated that the probability of adoption was higher in the mid-south area where the remote sensing service provider, InTime, Inc., started operating in 2003. Farmers who had irrigated cotton area had a 2.8% higher probability of adopting aerial or satellite imagery.

Adopters of remote sensing technology appeared to be much more technologically savvy than non-adopters, which had a large impact on the probability of adoption. Producers who used personal digital assistants or laptop computers in farm fields to make management decisions were 4.1% more likely to have used remotely sensed imagery. Farmers who made their own map-based prescriptions were 47.2% more likely to have used aerial or satellite imagery to make VRT decisions. Crop consultants also appeared to play an important role in the decision to adopt aerial or satellite imagery. Farmers who used consultants for map-based prescriptions had a 12.5% higher probability of using remote sensing to make VRT decisions.

Summary and Conclusions

This research evaluated the farm and farmer characteristics that influenced cotton producers to adopt remotely sensed imagery for variable rate application of inputs. Data from a 2005 mail survey of cotton producers in Alabama, Arkansas, Florida, Georgia, Louisiana, Mississippi, Missouri, North Carolina, South Carolina, Tennessee, and Virginia was used to specify a logit model for the adoption analysis. Farmers who were younger, more highly educated, had larger farm operations, or were more technologically savvy were more likely to have used aerial or satellite imagery to make VRT management decisions on their farm. Agribusiness input dealers were not an important (i.e., statistically significant) source for generating map-based prescription using the imagery data for remote sensing adopters. By contrast, crop consultants were a significant source for generating prescription maps for variable rate decision making using remote sensing. The results suggest that consultants may have been an important factor in the adoption of remote sensing technology by cotton farmers. However, the most important farmer characteristic influencing the probability of adoption of remote sensing was farmers who indicated that they generated their own map-based prescriptions for variable rate application of inputs using remote sensing imagery. One of the services of a major remote sensing provider in the area covered by the survey was the ability for clients to generate prescription maps via an internet site. Thus, it appears that the availability of value-added services by consultants and remote sensing providers may have a very important influence on farmers’ decision to adopt remote sensing.

Results from this remote sensing adoption analysis broach some socioeconomic issues. Variable rate decision making using remote sensing was not as prevalent among farms with smaller crop areas. Non-adopters also were less technologically savvy because they were less likely to use computers and related applications for crop decision making when compared with adopters. Thus, a potential barrier to adoption may be related to the technical skills needed to use computer applications necessary to make remotely sensed imagery useful for crop management.

Although the belief by respondents that Extension Service should provide more educational programs about precision farming was not found to affect adoption of remote sensing technologies, the fact that seven in ten respondents have this belief is notable for the remaining suite of technologies. Extension may have a role in providing computer training to farmers and crop consultants on how to use computers for collecting site-specific information and how to use computers for making prescription maps. There may also be a role for Extension in making and analyzing maps for smaller limited resource farmers.

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Table 1. Definition of variables and hypothesized impacts for the remote sensing adoption analysis

Variable	Mean	Sign	Definition
Dependent Variable			
REMOTE	0.08	NA	Used remotely sensed imagery to make at lease one variable rate technology (VRT) decision (1 if yes, 0 if no)[a]
Explanatory Variables			
Farm Characteristics			
ACRE	1.16	+	Total crop area (1,000s acres)
INCOME	0.35	+	Pre-tax household income (1 for income > $150,000, 0 if no)
IRRIGATE	0.34	+	Has irrigated cotton area (1 if yes, 0 if no)
LOCATION	0.54	+	Farm located in either Alabama, Arkansas, Louisiana, Mississippi, Missouri, or Tennessee (1 if yes, 0 if no)
Farmer Characteristics			
AGE	0.20	+	Younger than 40 years old (1 if yes, 0 if no)
EDUCATION	14	+	Formal education excluding kindergarten (years)
COMPUTER	0.14	+	Used a laptop or handheld computer in farm fields (1 if yes, 0 if no)
SELF	0.03	+	Generated own map-based input prescriptions (1 if yes, 0 if no)
CONSULT	0.05	+	Used a crop consultant to generate map-based input prescriptions (1 if yes, 0 if no)
DEALER	0.08	+	Used a dealer to generate map-based input prescriptions (1 if yes, 0 if no)
EXTENSION	0.70	−	Believes Extension needs to provide more information about precision farming (1 if yes, 0 if no)

[a] The VRT decisions were for fertility and lime, seed, plant growth regulators, harvest aids, fungicides, herbicides, insecticides, irrigation, identifying management zones, and mitigating drainage problems.

Table 2. Estimated logit model for adoption of remotely sensed imagery for site-specific management in cotton production

Explanatory Variable/ Statistic[a]	Coefficient	Marginal Effect[b]
CONSTANT	−6.288***	NA
	(0.976)	
ACRE	0.170**	0.009**
	(0.074)	(0.381)
INCOME	0.287	0.015
	(0.274)	(0.149)
IRRIGATE	0.521*	0.028*
	(0.272)	(0.016)
LOCATION	0.629**	0.031**
	(0.299)	(0.015)
AGE	0.583*	0.035*
	(0.299)	(0.21)
EDUCATION	0.148**	0.007**
	(0.062)	(0.003)
COMPUTER	0.651**	0.041*
	(0.313)	(0.024)
SELF	3.047***	0.472***
	(0.512)	(0.121)
CONSULT	1.397***	0.125**
	(0.383)	(0.054)
DEALER	0.161	0.009
	(0.434)	(0.025)
EXTENSION	0.154	0.008
	(0.313)	(0.015)
N	941	NA
Concordant	80.3%	NA
Discordant	19.0%	NA
Tied	0.7%	NA
Correctly Predicted	92.4%	NA
Likelihood Ratio	121.2***	NA

[a] Variables are defined in Table 2.

[b] Marginal effects of the continuous variables were calculated by differentiating the probabilities with respect to the explanatory variables. Marginal effects of the dummy variables were computed as $Pr(y = 1|d = 1) - Pr(y = 1|d = 0)$, where y=1 if remote sensing technology is adopted by farmer and d is the dummy variable.

Note: Standard errors for the estimated coefficients are in parentheses. ***,**, and * indicate significance at the 1%, 5%, and 10% levels, respectively. NA=Not applicable.