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Factors affecting farmer adoption of remotely sensed imagery for precision management in cotton production

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Abstract This research evaluated the factors that influenced cotton (*Gossypium hirsutum* L.) producers to adopt remote sensing for variable-rate application of inputs. A logit model estimated with data from a 2005 mail survey of cotton producers in 11 southern USA states was used to evaluate the adoption of remote sensing. The most frequently made management decisions using remote sensing were the application of plant growth regulators, the identification of drainage problems and the management of harvest aids. A producer who was younger, more highly educated and had a larger farm with irrigated cotton was more likely to adopt remote sensing. In addition, farmers who used portable computers in fields and produced their own map-based prescriptions had a greater probability of using remote sensing. The results suggest that value-added map-making services from imagery providers greatly increased the likelihood of a farmer being a user of remote sensing.

Keywords Aerial imagery · Precision farming technology · Satellite imagery · Variable-rate technology

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Introduction

A site-specific management technology that is showing considerable potential in agriculture is aerial or satellite (passive remotely sensed) imagery (Pinter et al. 2003). Sunlight reflected off the surfaces of crops and soil can be recorded by aerial or satellite imagery and used to identify different characteristics of the vegetation or soil. Reflectance data obtained with remote sensing (RS) can be used in crop management when it is related to a measure of the growing plant canopy such as leaf area index or percentage ground cover (Hong et al. 2001). One commonly used measure of the growing plant canopy is the normalized difference vegetation index (NDVI) (Ashley and Rea 1975). Remote sensing can provide spatially distributed reflectance data on plant growth and development at different stages of the growing season that might be useful for tactical and strategic site-specific management of the growing crop (Plant et al. 2001; Zarco-Tejada et al. 2005). It can also be used on bare soil to identify soil characteristics in fields (Dalal and Henry 1986).

The ability to do in-season monitoring and management of the growing crop is particularly important in cotton production. Farmers (or consultants) often use the stage of cotton plant growth and development to time the application of inputs such as irrigation water, plant growth regulators, pesticides and harvest aids (i.e. defoliants and or desiccants to prepare the crop for harvest) (Bourland et al. 1992). Thus, RS 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. In addition, cotton is a high value crop that requires extensive use of fertilizers and chemicals (Brooks 2001). Moreover, cotton produced in the southern USA is often grown on fields that have heterogeneous soil (Mallarino and Wittry 2004). Thus, cotton production that relies on high inputs might be well suited to in-season, site-specific management using RS.

The use of RS for cotton production has been increasing with the introduction of new aerial imaging services that target in-season, site-specific management of the crop. For example, InTime, Inc. started offering aerial imaging services specifically for cotton in 2003. This company reported that 26 305 ha (65 000 acres) of cotton were imaged using its service in the mid-south region of the USA in 2003 (InTime Inc. 2007), and that area increased to about 101 174 ha (250 000 acres) in 2004 (InTime Inc. 2007). The company currently (2007) offers its services in 12 states. InTime, Inc. provides digitally processed maps at the field level at frequent intervals during the growing season to subscribers via an Internet website. Subscribers (e.g. farmers or crop consultants) to the service can make prescription maps and download them to a variable-rate technology (VRT) controller for the application of inputs. As further evidence of growth in this market, in 2005 John Deere Agri Services introduced an aerial imagery service similar to InTime to provide RS images, prescription maps and other consulting services to cotton farmers (Brown and Wesch 2006).

Agronomic and economic research evaluating the use of RS in site-specific management for cotton has focused primarily on management of plant population density, nutrients, water, pests, plant growth regulators and harvest aids (e.g. Kirpatrick et al. 2005; Larson et al. 2004; Plant and Monk 1999a, b; Willers et al. 2005; Zarco-Tejada et al. 2005). However, there has been little research on the actual use of RS by farmers in site-specific cotton management and the factors that influence producers to adopt aerial or satellite imagery have not been investigated. Thus, our research objectives were (1) to document the use of RS in cotton production for site-specific management decisions and (2) to determine the factors that influence cotton producers to adopt RS for VRT application of inputs.

Materials and methods

Data

A mail survey of cotton producers in 11 southern states in the USA was conducted in 2005 to obtain information about their attitudes toward, and their use of, precision farming technologies (Cochran et al. 2006). Following Dillman's (1978) procedures for mail surveys, the questionnaire, a postage-paid return envelope and a covering letter explaining the purpose of the survey were sent to each producer on 28 January 2005. A reminder post-card was sent 1 week later on 4 February 2005, and a follow-up mailing to non-respondents was sent 3 weeks later on 23 February 2005. The second mailing included a letter reiterating the importance of the survey, the questionnaire and a postage-paid return envelope. Of the 12 243 questionnaires sent out, 18 were returned as undeliverable and 182 respondants indicated that they were not cotton farmers or had retired, leaving a total population of 12 043 cotton producers. Of those cotton producers, 1 215 provided complete data to give a usable response rate of 10% (Cochran et al. 2006).

Data describing the characteristics of the farm's decision maker and its 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 decisions were for fertility and or lime, seed, plant growth regulators, harvest aids, fungicides, herbicides, insecticides and irrigation. In addition, farmers were asked whether they used RS for mitigating drainage problems. A farmer was defined as an adopter of RS if that individual reported using the technology for one or more of the aforementioned VRT decisions. Data on the use of other precision farming technologies and related services, and sources of information were also collected. A total of 98 (8%) of the 1215 farmers who responded to the survey indicated that they used RS for VRT decision-making in their cotton operation (Table 1). Additional information about the survey is available upon request from the authors (Cochran et al. 2006).

The data from the adopters were used to describe farmers' use of RS for alternative VRT decisions and to specify a binomial logit model to determine what farmer and farm characteristics influenced the decision to adopt (see Kennedy 2003 for more on logit models). The number of usable responses for the logit model analysis was reduced from 1 215 to 941 because of missing data. Of the 941 observations, 77 were considered adopters of RS technologies for VRT application of inputs. The area under cotton for the 77 adopters used in the logit model was 49 260 ha (121 721 acres) compared with 56 706 ha (140 120 acres) for the 98 adopters in the original data set.

Analytical framework

The random utility model was used to analyze the decision to adopt or not adopt RS technology (see Kennedy 2003, for example). 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 observed directly. Thus, the utility function for decision maker n is given by:

Table 1 Variable-rate technology (VRT) decisions made by cotton farmers who used remotely sensed imagery

Item	Number	Percentage[a]
Remote sensing adopters (i.e. respondents who used aerial or satellite imagery for one or more VRT decisions)	98	8
Cotton area planted (Irrigated and non-irrigated ha)	56 706	15
Other information technologies used		
Cotton yield monitor (CYM)	44	43
Handheld GPS/PDA units (PDA)	40	39
COTMAN plant mapping expert system (COTMAN)	12	12
CYM and PDA	11	11
CYM and COTMAN	11	11
PDA and COTMAN	11	11
CYM, PDA and COTMAN	10	10
VRT input decisions using remote sensing		
Drainage	49	50
Fertility and or lime	40	41
Seeding	15	15
Plant growth regulator	52	53
Harvest aids	46	47
Fungicide	16	16
Herbicide	14	14
Insecticide	31	32
Irrigation	19	19
Average VRT decisions made with remote sensing	3.26	NA

NA = Not applicable

[a] The percentage for the first two statistics is based on the 1 215 total survey respondents. The percentage of the remainder are based on the sample of remote sensing adopters ($n = 98$)

$$U_n = V_n + \varepsilon_n = \boldsymbol{\beta}'\mathbf{x}_n + \varepsilon_n, \tag{1}$$

where U is the utility from adopting RS technology by farmer n, V is the deterministic portion of utility, ε is the random error term, $\boldsymbol{\beta}$ is a $k \times 1$ vector of parameters to be estimated, $\mathbf{x}$ is a $k \times 1$ vector of explanatory variables that are assumed to affect a farmer's decision to adopt RS technology. Let y represent the unobserved utility from the adoption choice where y equals 1 if the technology is adopted and 0 if it is not. A farmer chooses to adopt RS 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 RS is:

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

Given the random utility framework for the decision to adopt RS, a binomial logit model that specifies the probability of this is:

$$P(y=1) = \frac{e^{\boldsymbol{\beta}'\mathbf{X}}}{1+e^{\boldsymbol{\beta}'\mathbf{X}}}, \tag{4}$$

where $\boldsymbol{\beta}$ is a $k \times 1$ vector of parameters to be estimated and $\mathbf{X}$ is an $N \times k$ matrix of explanatory variables. The probability of not adopting RS is:

$$P(y=0) = 1 - P(y=1) = \frac{1}{1+e^{\boldsymbol{\beta}'\mathbf{X}}}. \tag{5}$$

The logistic function in Eqs. 4 and 5 has a similar shape to the cumulative normal distribution and facilitates the modeling of probabilities within the 0–1 interval. The likelihood function that is formed using Eqs. 4 and 5 is:

$$\ell(\boldsymbol{\beta}|y,x) = \prod_{y=1} \frac{e^{\boldsymbol{\beta}'\mathbf{X}}}{1+e^{\boldsymbol{\beta}'\mathbf{X}}} \prod_{y=0} \frac{1}{1+e^{\boldsymbol{\beta}'\mathbf{X}}}. \tag{6}$$

Estimates of the coefficients were found by maximizing the log of the likelihood function using the method of maximum likelihood. Once estimates of the coefficients were obtained, the probability that a specific farmer was observed to have adopted RS technology could be predicted. The significance and magnitude of the parameter estimates were also used to identify factors that might influence a farmer's decision to adopt RS.

Empirical model

Binomial logit model

A review of the literature on the adoption of precision agriculture was used to identify the characteristics of the farmer and the farm operation that might influence adoption of RS (e.g., Batte and Arnholt 2003; Daberkow et al. 2003; Khanna 2001; Napier et al. 2000; Popp and Griffin 2001; Roberts et al. 2004; Torbett et al. 2007). Using information from these sources, the following binomial logit model was specified:

$$\begin{aligned} \text{REMOTE}_n = \beta_0 &+ \beta_1\text{AREA}_n + \beta_2\text{INCOME}_n + \beta_3\text{IRRIGATE}_n + \beta_4\text{LOCATION}_n \\ &+ \beta_5\text{AGE}_n + \beta_6\text{EDUCATION}_n + \beta_7\text{COMPUTER}_n + \beta_8\text{SELF}_n \\ &+ \beta_9\text{CONSULT}_n + \beta_{10}\text{DEALER}_n + \beta_{11}\text{EXTENSION}_n + \varepsilon_n, \end{aligned} \tag{7}$$

where β_k are $k = 0,\ldots,11$ parameters to be estimated using maximum likelihood, ε is the random error term, and n represents the nth farmer in the data. The variable definitions, hypotheses and means are given in Table 2.

Hypotheses

Farmers with a larger crop area (AREA) are more likely to observe spatial variation in their fields. Remote sensing might also be a labor saving technology for bigger farms by facilitating the identification of problem areas to be investigated rather than walking the whole field. In addition, cotton producers with a larger crop area are more likely to have in place already a package of management practices and technologies that could be used with RS to further enhance productivity (Barham et al. 2004). Thus, larger farms are expected to have a greater probability of adoption. Farmers with larger household income (INCOME)

Table 2 Definition of variables and assumed impacts for the remote sensing adoption analysis

Variable	Mean	Expected sign[a]	Definition
Dependent variable			
REMOTE	0.08	NA	Used remotely sensed imagery to make at least one VRT decision (yes = 1, no = 0)
Explanatory variables			
Farm characteristics			
AREA	1.16	+	Total crop area (405 ha units)
INCOME	0.35	+	2004 Pre-tax household income > $150 000 (yes = 1, no = 0)
IRRIGATE	0.34	+	Has irrigated cotton area (yes = 1, no = 0)
LOCATION	0.54	+	Farm located in either Alabama, Arkansas, Louisiana, Mississippi, Missouri or Tennessee (yes = 1, no = 0)
Farmer characteristics			
AGE	0.22	+	Less than 40 years old (yes = 1, no = 0)
EDUCATION	14	+	Formal education excluding kindergarten (years)
COMPUTER	0.14	+	Used a laptop or handheld computer in fields (yes = 1, no = 0)
SELF[b]	0.03	+	Generated own map-based input prescriptions (yes = 1, no = 0)
CONSULT[b]	0.05	+	Used a crop consultant to generate map-based input prescriptions (yes = 1, no = 0)
DEALER[b]	0.08	+	Used a fertilizer and chemical dealer to generate map-based input prescriptions (yes = 1, no = 0)
EXTENSION	0.54	+	Believed that information from Extension and Universities was useful in making decisions about precision farming (yes = 1, no = 0)

[a] The hypothesized sign on the estimated coefficient indicates whether the explanatory variable was expected to have a positive or negative impact on the probability of a cotton farmer adopting remote sensing

[b] The SELF, CONSULT, and DEALER explanatory variables came from a survey question that asked farmers who indicated that they used map-based methods to apply inputs, who typically generates the maps and information to apply inputs. The choices were the farm decision maker (SELF), a consultant (CONSULT), or a fertilizer and chemical dealer (DEALER), or none of these. Farmers were asked to select the choice that most applies to them (Cochran et al. 2006). The explanatory variable representing the category that included farmers who did not use map-based variable-rate technology was dropped to avoid perfect multicollinearity problems when estimating the logit model

may be more able to invest in site-specific technology and services and, thus, may also have a greater probability of adoption.

The presence of irrigated cotton (IRRIGATE) might also affect the probability of adopting RS. Yields for irrigated cotton are generally larger than for dryland cotton and may be associated with higher inputs. Thus, there might be more opportunities to vary inputs with crop needs in different parts of fields under irrigation. In addition, RS can also be used for non-VRT related crop decisions. For example, the reflectance data could be used to assess crop water status to time irrigations (Ritchie et al. 2005). Irrigated cotton production has become more common in the states covered by this survey and could be a factor in the adoption of RS (USDA, NASS 2004); in particular, we expect those with irrigated areas to have a higher probability of adoption.

The location of a farm might also influence the decision to adopt RS. At the time of the survey, InTime, Inc.'s RS operation was based in Cleveland, MS, USA (south of Memphis, TN, USA) with a branch office in Courtland, AL, USA (located in northern Alabama south of Nashville, TN, USA) (Robinson 2004). The locations of farms were modeled using a dummy variable (LOCATION) to test whether farmers in Alabama, Arkansas, Louisiana, Mississippi, Missouri and Tennessee had a higher probability of adopting RS than those in Florida, Georgia, North Carolina, South Carolina and Virginia. The potential difference among these two regions was expected to be related to the availability of RS and other precision technologies and services from agribusiness providers. The mid-south states represented by LOCATION = 1 encompass the initial area where RS services were offered by InTime, Inc.

The following characteristics of the farm's decision maker were assumed to influence the RS adoption decision. A younger farmer (AGE) may have a longer planning horizon, more exposure to new technologies and be more motivated to try new technologies compared to an older farmer. These characteristics suggest that younger farmers are less risk averse, which would have a positive impact on farmers' perceptions of RS technology. Implementation of site-specific management on 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 evaluate and implement site-specific management successfully.

The productivity enhancing effects of site-specific technology might be only fully realized when a package of management practices and technologies are in place (Barham et al. 2004). Computer technology, another important aspect of site-specific management, is likely to be an important component in a technology package that includes RS. Thus, farmers who use computers in farm management and, in particular, in their fields were expected to be more likely to adopt RS than those who do not. An important element of successfully utilizing RS for VRT decision-making is the process of "ground truthing" the data to verify problems and identify areas that require treatment (Robinson 2006). One method of ground truthing is to examine the potential problem areas identified on the RS 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 fields was expected to be positively associated with the adoption of RS technology.

Another important aspect of a package for site-specific management is the analysis of spatial field data and the creation of prescription maps for VRT application. A crop consultant or fertilizer and chemical dealer promoting services such as VRT map-making or application might influence a farmer to purchase a subscription for RS. In addition, the recent availability of user-friendly web-based tools for making prescription maps, such as those offered by InTime, Inc., facilitate the creation of prescription maps for independent consultants or farmers themselves. Thus, farmers' use of other technologies and services might play an important role in explaining the decision to adopt RS. In the 2005 survey, farmers who indicated that they used map-based methods to apply inputs using VRT were asked who typically generates the maps and information to apply inputs. The choices were a crop consultant (CONSULT), a fertilizer and chemical dealer (DEALER) and the farm decision maker (SELF). Farmers were asked to select the one that most applies to them (Cochran et al. 2006). The explanatory variable representing the category that included farmers who did not use map-based VRT was dropped to avoid perfect multicollinearity problems when estimating the logit model. The CONSULT and DEALER explanatory variables were proxies for potential value-added services that might be part of a package of services that include RS (Barham et al. 2004). The SELF explanatory variable was a proxy for the availability of RS services in the area covered by the survey that enable clients to generate field and VRT prescription maps via an internet site. Based on the above discussion, these three variables were expected to have a positive effect on the probability of a farmer adopting RS technology compared to a farmer who did not have one of these characteristics.

Finally, the perceptions of precision farming educational programs of the Extension Service and Universities and their impact on RS adoption were embodied in the EXTENSION variable. Farmers who felt that information from the Extension Service and universities was useful in making precision farming decisions were expected to be more likely to adopt RS. Producers might view advice and information from these sources as being unbiased. Information from these sources might also be thought of as an important part of a technology package that includes RS. In addition, the availability of information from the Extension Service and universities might reduce some of the perceived risk associated with adoption of RS technology.

Logit model estimation and testing

The unknown parameters in Eq. 7 were estimated using SAS (SAS Institute Inc. 2004). Odds ratios (Cody and Smith 2005) were calculated to facilitate the interpretation of the logit model using:

$$\mathrm{ODDS} = \frac{P(y=1)}{1-P(y=1)} = e^{\boldsymbol{\beta}'\mathbf{X}}, \tag{8}$$

where $P(y = 1)$ is the probability of adopting RS, $\boldsymbol{\beta}$ is a $k \times 1$ vector of estimated parameters and $\mathbf{X}$ is an $N \times k$ matrix of explanatory variables. Equation 8 was used to evaluate how the odds of being an adopter of RS vary as the explanatory variable of interest changes. In addition, the odds ratios for specific sets of farmer and farmer operation characteristics were used to evaluate which factors most influenced the probability of adopting RS technology. The probability of adoption was calculated by:

$$P(y=1) = \frac{\mathrm{ODDS}}{1+\mathrm{ODDS}}. \tag{9}$$

The presence of multicollinearity among the explanatory variables in Eq. 7 could have a negative effect on the significance and inferential power of the estimated coefficients. Therefore, diagnostic tests for multicollinearity were performed using procedures outlined by Belsley et al. (1980).

In addition, several explanatory variables might be correlated with the error term ε in Eq. 7. If one or more of the explanatory variables are correlated with the error term (i.e. an endogenous variable), this violates one of the basic assumptions of econometric models that the explanatory variables are uncorrelated with the error term (i.e. an exogenous variable). This is because site-specific management technologies are often adopted sequentially or as packages (Khanna 2001; Roberts et al. 2004). If so, the productivity enhancing effects of an agricultural technology might be fully realized only on farms that already have in place a package of complimentary management practices and advanced technologies, such as RS (Barham et al. 2004). Given that larger farm operations are more likely to have these packages in place, the decision to adopt RS might not be independent of the COMPUTER, SELF, CONSULT, DEALER, AREA and INCOME explanatory variables. The test for potential correlations of suspect explanatory variables with the error term in the logit model was done with the procedure outlined by Rivers and Vuong (1988). Each of the explanatory variables believed to be correlated with the error term was regressed against all the other explanatory variables believed to be uncorrelated with the error term, and a vector of explanatory variables known to be uncorrelated with the error term. The residuals from these equations were then included as additional explanatory variables in a separate estimation of the adoption equation. The estimated coefficients for the residual explanatory variables were tested for joint significance using a Wald test (Wooldridge 2002). The joint (null) hypothesis is that COMPUTER, SELF, CONSULT, DEALER, AREA and INCOME are not correlated with the error term. Failure to reject the null hypothesis of joint significance provides evidence that the explanatory variables are not correlated with the error term in the logit model.

Results and discussion

Description of the sample data

The area under cotton reported by the 98 RS adopters in the survey was 56 706 ha (140 120 acres); this was 15% of the total cotton area reported by all farmers in the sample (Table 1). A large proportion of RS adopters also used other information technologies to make VRT decisions, such as cotton yield monitors and handheld GPS or PDA units. Adopters made an average of 3.26 VRT decisions using imagery. The most frequently made of these were the application of plant growth regulators (53% of adopters), the identification of drainage problems (50% of adopters), the application of harvest aids (47% of adopters) and the application of fertilizer and or lime (41% of adopters). Remote sensing adopters were least likely to use the information for VRT irrigation (19% of adopters), VRT fungicide applications (16% of adopters), VRT seeding decisions (15% of adopters) and VRT herbicide applications (14% of adopters).

Logit model

Estimation and testing

The estimated logit model is given in Table 3. The likelihood ratio statistic of 129 (Table 3) was statistically significant at the 1% level (11 d.f.), which indicates that the model explained a significant proportion of the variance in the adoption of RS by cotton farmers. The percentages of concordant and discordant pairs of observations with different responses are 81.6 and 17.7%, respectively, with 0.7% ties (Table 3). The concordant rate indicates an acceptable prediction rate. The model correctly predicted 92.6% of farmer's responses overall (66.2% for adopters and 93.2% for non-adopters) (Table 3).

Diagnostic tests for multicollinearity indicated potential problems with the intercept (CONSTANT) and farmer education (EDUCATION) variables (not shown). However, CONSTANT and EDUCATION were statistically significant (Table 3) at the 1 and 5% probability levels, respectively, indicating that the standard errors for the variables were not seriously degraded by multicollinearity (Belsley et al. 1980). For the test of endogeneity, the Wald test had a chi-square value of 5.34 with $p = 0.38$. This test resulted in failure to reject the joint (null) hypothesis that COMPUTER, SELF, CONSULT,

Table 3 Estimated logit model for the adoption of remotely sensed imagery for site-specific management in cotton production (REMOTE)

Explanatory variable or statistic	Coefficient[a]	Odds ratio
CONSTANT	−6.569*** (1.005)	NA
AREA	0.159** (0.077)	1.169
INCOME	0.275 (0.283)	1.317
IRRIGATE	0.582** (0.281)	1.789
LOCATION	0.743** (0.315)	2.101
AGE	0.568* (0.303)	1.765
EDUCATION	0.136** (0.064)	1.145
COMPUTER	0.738** (0.319)	2.091
SELF	3.170*** (0.517)	23.81
CONSULT	1.386*** (0.402)	4.000
DEALER	0.277 (0.438)	1.319
EXTENSION	0.592** (0.293)	1.807
N	941	NA
Concordant	81.6%	NA
Discordant	17.7%	NA
Tied	0.7%	NA
Correctly predicted		
Overall	92.6%	NA
Adopters	66.2%	NA
Non-adopters	93.2%	NA
Likelihood ratio	129.0***	NA

NA = Not applicable

***, **, * indicate significance at the 1, 5, and 10% levels, respectively

[a] Parentheses contain the standard errors associated with the parameter above

DEALER, AREA and INCOME were exogenous explanatory variables. Thus, the single equation logit model was deemed appropriate for the analysis.

Empirical results

The only explanatory variables in the logit model given in Table 3 that did not help to explain the adoption of RS were a large household income (INCOME) and the farmer's use of a fertilizer or chemical dealer to generate maps and information to apply inputs using

VRT (DEALER). All of the other explanatory variables in the logit model given in Table 3 were statistically significant and had the hypothesized relationships (i.e. had positive signs on the estimated coefficients) with RS adoption (Table 2). A cotton grower who was younger, more highly educated and had a larger crop area was more likely to have used RS to make VRT management decisions. More specifically, a farmer who was less than 40 years old was 1.8 times more likely to be an adopter of RS than a producer who was 40 years or older (Table 3). Based on a mean education of 14 years in the sample (Table 2) and the estimated coefficient for EDUCATION (Table 3), a farmer with two additional years of education (about the equivalent of a 4 year college education) was $1.3 = (e^{0.136})^2$ times more likely to be a user of RS. Based on a mean crop area of 1.16 (in 405 ha units)(Table 2) and the estimated coefficient for AREA (Table 3), the odds of adopting RS was $1.4 = (e^{0.159})^2$ times greater for a farm with about twice as much crop area. The results indicate that whereas education and farm size were significant explanatory variables, their effect on the probability of a farmer adopting RS technology were small.

Two characteristics of the farm operation, the location of the farm (LOCATION) and the presence of irrigated cotton (IRRIGATE), had positive impacts on the probability of a farmer adopting RS technology (Table 3). A cotton farmer in Alabama, Arkansas, Louisiana, Mississippi, Missouri or Tennessee was 2.1 times more likely to be a user of RS than a producer in Florida, Georgia, North Carolina, South Carolina and Virginia. The results indicate that the odds of adoption were greater in the mid-south area where the RS service provider, InTime, Inc., started operating in 2003. In addition, a farmer who had irrigated cotton was 1.8 times more likely to adopt RS than a producer who did not (Table 3). Although farmers in the survey did not cite irrigation as one of the most frequently made VRT decisions using RS (Table 1), producers with irrigated cotton might have used more inputs and have had more opportunities to vary inputs with crop needs in different areas of the fields under irrigation.

Explanatory variables describing farmers' use of other technologies and services that may complement RS also had positive effects on the probability of a farmer adopting RS. For a farmer who used a personal digital assistant or laptop computer in fields for crop management (COMPUTER), the odds of being an adopter of RS was 2.1 times higher than for a farmer who did not use such devices (Table 3). Thus, the results suggest that a farmer's use of portable computers was an important part of the technology package that included RS. Such devices might have been used by adopters for "ground truthing" RS data to verify problems and identify areas that require treatment. In addition, a cotton producer who believed that information from the Extension Service and Universities was useful in site-specific management was 1.8 times more likely than others to adopt RS (Table 3). Thus, site-specific management education programs created by the Extension Service and Universities had a positive impact on the probability of a farmer being a user of RS.

However, the two explanatory variables that had the largest impacts on the likelihood of a farmer using of RS were CONSULT and SELF. A farmer who used a crop consultant to generate maps and information for VRT application (CONSULT) was four times more likely to use RS to make VRT decisions than a producer who was not in the CONSULT, DEALER or SELF categories (Table 3). By comparison, a cotton grower who generated his or her own maps and information for VRT inputs (SELF) was 23.8 times more likely to have used RS than a grower who was not in these categories (Table 3). Thus, crop consultants may have played a key role in some farmers' decisions to adopt RS, most likely through the provision of services such as map-making and VRT prescription information that are complementary to the imagery. The SELF explanatory variable probably embodies the influence of increased availability of user-friendly web-based tools that farmers can use directly for making maps and VRT prescriptions such as those offered by InTime, Inc. The results indicate that SELF had the largest impact of all the explanatory variables on the probability of a producer adopting RS technology. The DEALER explanatory variable might not have been significant because fertilizer and chemical dealers may focus more on providing maps and VRT recommendations based on soil testing data rather than RS data (Table 3).

The estimated probability of a farmer using RS was evaluated for several combinations of explanatory variables using the estimated coefficients given in Table 3. The two non-significant dummy variables, INCOME and DEALER, were set equal to zero for calculating probabilities. For the first example, the levels of education (EDUCATION) and crop area (AREA) were set at their sample means (Table 2) and the values of the other significant dummy variables in the logit model were set equal to zero, i.e., IRRIGATE = 0, LOCATION = 0, AGE = 0, COMPUTER = 0, SELF = 0, CONSULT = 0 and EXTENSION = 0. Under this scenario, the predicted probability of a farmer using imagery was only 1%, or essentially zero.

For the second scenario, EDUCATION and AREA were set at their sample means and all of the aforementioned significant dummy variables were set to 1 except for SELF. Thus, the second case represents a younger cotton farmer in the mid-south region who had irrigated cotton, used a computer in the field, used a consultant to generate maps and information for VRT input application (CONSULT), and believed that Extension information on site-specific management was useful. The probability of being an adopter of RS technology for a farmer with this set of characteristics was 54%. For the second scenario, setting EXTENTION = 0 reduced the probability of being an adopter from 54 to 35% assuming that all of the other farmer and farm characteristics stayed the same. The results indicate that the probability of a producer adopting imagery was greater for a farmer who had a positive perception about the usefulness of Extension information for site-specific management.

For the third example, CONSULT = 0 and SELF = 1 to represent a farmer with the same set of characteristics as in the second scenario except that he or she primarily generated their own maps and information for VRT application rather than relying primarily on a consultant. The probability of a farmer adopting RS technology under this scenario rose to 87%. The results from the logit model indicate that a farmer who uses computers and mapping software for crop management might be more able to exploit fully the productivity enhancing potential of RS. Thus, a cotton producer who had the attribute represented by SELF had a much higher probability of using RS than a farmer who did not have the characteristic.

Conclusions

The results of this study suggest that value-added services provided by crop consultants and RS service providers may have been an important factor in explaining the adoption of aerial or satellite imagery by cotton growers in 11 southern states in the USA. These value-added services may be part of a total site-specific management package that includes RS. One of the services available from a major RS provider in the study area was the ability for farmers and consultants to generate field and VRT prescription maps from imagery via an Internet site. The increased availability of value-added services from aerial or satellite providers in the study area appears to have had a large impact on the probability of a cotton grower adopting of RS. In addition, the results suggest that a farmer who used computers and mapping software for crop management may be able to exploit more fully the productivity enhancing potential of RS. Thus, a cotton grower with these abilities was more likely to use aerial or satellite imagery. Finally, Extension might have a role in training farmers and crop consultants to use computers for obtaining and analyzing site-specific information, and for making prescription maps. Cotton growers with these skills may be more able to exploit the productivity enhancing potential of RS.

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