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**Adoption of Spatial Information Gathering Technologies and Variable Rate Input
Application Technologies by Cotton Farmers in the Southeast**

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Adoption of Spatial Information Gathering Technologies and Variable Rate Input Application Technologies by Cotton Farmers in the Southeast

Abstract

Probit analysis identified factors influencing adoption of precision farming technologies by Southeastern cotton farmers. Younger, more educated farmers who operated larger farms and were optimistic about the future of precision farming were most likely to adopt site-specific information technology. The probability of adopting variable rate input application technology was higher for younger farmers who operated larger farms, owned more of the land they farmed, were more informed about the costs and benefits of precision farming, and were optimistic about the future of precision farming. Computer use was not important possibly because custom hiring shifts the burden of computer use to agribusiness firms.

Introduction

Several site-specific information technologies are available to help farmers develop prescriptions for variable rate application of production inputs (National Research Council). These site-specific information technologies range from satellite imagery to grid soil sampling to soil survey maps. Even without variable rate application of inputs, these technologies provide farmers with a wealth of information about their fields for making more informed production decisions (Batte and Arnholt; Jaenicke and Cohen-Vogel; Khanna). Nevertheless, information about variation in physical and chemical properties of soil across a field is a prerequisite for efficient variable rate input application. Properly specifying the sequential adoption relationship between site-specific information and variable rate technologies, and using appropriate statistical methods for analysis of technology adoption decisions, are essential for meaningful research on the adoption of precision farming technologies.

Khanna reviewed literature on technology adoption, and more specifically, precision farming technology adoption, in her evaluation of the sequential adoption of site-specific information and variable rate technologies. Additional literature on precision farming technology adoption can be grouped by studies that either 1) discussed or evaluated factors influencing adoption using survey results (Arnholt, Batte, and Prochaska; Batte and Arnholt; Daberkow and McBride; Daberkow, Fernandez-Cornejo, and Padgitt, 2002a; Maohua; Norton and Swinton; Plant; Popp and Griffin; Roberts et al.; Swinton and Lowenberg-DeBoer, 2001; Whipker and Akridge), 2) simulated adoption decisions using option-value models and dynamic programming (Daberkow, Fernandez-Cornejo, and Padgitt, 2002b; Jaenicke and Cohen-Vogel; Isik, Khanna, and Winter-Nelson), or 3) used limited dependent variable or discriminant analysis to determine the characteristics of adopters (Fernandez-Cornejo, Daberkow, and McBride; Napier, Robinson, and Tucker; Roberts, English, and Larson). While Khanna's research evaluated the adoption of soil testing (not necessarily site-specific soil testing) and variable rate application of fertilizer and/or lime by cash-grain farmers in four Midwestern states, our research concentrates on the sequential adoption of a broader array of site-specific information and variable rate technologies for the production of a single crop, cotton, in six Southeastern states.

Our objective was to determine the farm and farmer characteristics that influence Southeastern cotton farmers to adopt site-specific information and variable rate technologies for cotton production. High-value, high-input crops, such as cotton, have potential for profitable precision farming (Swinton and Lowenberg-DeBoer, 1998). Identifying these characteristics could help extension personnel target their education and training programs toward farmers who are most likely to adopt these technologies and benefit from their programs. In addition, agribusiness firms could use this research to develop promotional

efforts directed toward farmers who are most likely to benefit from adopting these technologies and, thus, purchase their products.

Analytical Framework

Let U_s be the expected utility accruing to a farmer from gathering site-specific information necessary to make the variable rate technology (VRT) versus uniform rate technology (URT) input application decision and let $U_{v|s}$ and $U_{u|s}$ be the respective expected utilities from using VRT or URT given that site-specific information was gathered. Further, let U_w be the expected utility accruing to the farmer from gathering whole-field information. Defining $U_s^* = U_s - U_w$ and $U_v^* = U_{v|s} - U_{u|s}$, the farmer who maximizes expected utility will choose to:

- (1) gather site-specific information and use VRT when $U_s^* > 0$ and $U_v^* > 0$,
- (2) gather site-specific information and use URT when $U_s^* > 0$ and $U_v^* < 0$, or
- (3) gather whole-field information and use URT when $U_s^* < 0$.

Gathering whole-field information and using VRT is not an option because the farmer has chosen not to gather the site-specific information necessary for VRT adoption.

By choosing to gather site-specific information, the farmer is self-selected into the sample of farmers who can choose between VRT and URT. This property implies the use of methods that account for sample selection (Greene, 2003; Hausman and Wise). As in Khanna, the unobservable latent variables, U_s^* and U_v^* , are assumed to be random functions of observable vectors of exogenous variables Z_s and Z_v ,

$$(4) \quad U_s^* = Z_s \gamma_s + \epsilon_s, \quad U_v^* = Z_v \gamma_v + \epsilon_v,$$

where γ_s and γ_v are vectors of unknown parameters and ϵ_s and ϵ_v are random errors.

Although U_s^* and U_v^* are not observed, a farmer's decisions can be characterized as observable zero-one variables,

$$(5) \quad I_s = 1 \text{ if } U_s^* > 0, I_s = 0 \text{ otherwise,}$$

$$(6) \quad I_v = 1 \text{ if } U_v^* > 0 \text{ and } I_s = 1, I_v = 0 \text{ otherwise.}$$

The probabilities of occurrence for the choices characterized by Equations (1) through (3) can be written in terms of the variables given in Equations (5) and (6) (Greene, 2003 and 1998a),

$$(7) \quad \Pr(I_s = 1; I_v = 1) = \Pr(I_v = 1 \mid I_s = 1) \times \Pr(I_s = 1) = \Phi_2(Z_s\gamma_s, Z_v\gamma_v, \rho),$$

$$(8) \quad \Pr(I_s = 1; I_v = 0) = \Phi(Z_s\gamma_s) - \Pr(I_s = 1; I_v = 1) = \Phi_2(Z_s\gamma_s, -Z_v\gamma_v, -\rho),$$

$$(9) \quad \Pr(I_s = 0) = 1 - \Phi(Z_s\gamma_s) = \Phi(-Z_s\gamma_s),$$

where Φ_2 and Φ are cumulative distribution functions for the standard bivariate normal and standard normal distributions, respectively, and ρ is the correlation between ε_s and ε_v .

If ρ is not zero, Equations (5) and (6) form a system of equations that can be estimated with maximum likelihood as a bivariate probit model with sample selection. If ρ equals zero, the bivariate distribution reduces to the product of two univariate distributions. Thus, Equations (5) and (6) can be estimated as separate binomial probit models (Greene, 1998a); Equation (5) estimated with the full sample of observations ($I_s = 0$ and $I_s = 1$) and Equation (6) estimated with the observations for those farmers who selected themselves into the sub-sample of farmers eligible to make the VRT versus URT decision ($I_s = 1$ only).

Data

Data for the 1999-2000 season were collected from a mail survey of cotton farmers in Alabama, Florida, Georgia, Mississippi, North Carolina, and Tennessee conducted in January and February 2001 (Roberts et al.). Of the 5,976 cotton farmers who received the questionnaire, 1,131 (19%) responded by providing information about their adoption of precision farming technologies. Farmers were asked to indicate whether they had used the following site-specific information technologies for cotton production: yield monitoring with GPS (Global Positioning Systems); yield monitoring without GPS; grid soil sampling; management zone soil sampling; aerial photography; satellite imagery; soil survey maps;

mapping topography, slope, soil depth, etc.; plant tissue testing; and on-the-go sensing. Farmers also were asked to indicate whether they had used variable rate application technologies for the following inputs: nitrogen, phosphorus and potassium, lime, seed, growth regulator, defoliant, fungicide, herbicide, insecticide, and irrigation.

The number of usable responses was reduced from 1,131 to 789 because of missing data, and reduced further to 773 to eliminate respondents who reported adoption before the precision farming technologies became available for use on their farms. Some farmers reported using precision farming technologies for as many as 40 years, which suggests that they were using a definition of “precision farming” substantially different from the one used in this study. To maintain internal consistency, responses were eliminated for cotton farmers who reported using: 1) a cotton yield monitor with or without GPS for more than five years, or 2) variable rate nitrogen, phosphorous and potassium, or lime application for more than nine years.

Empirical Model

Dependent Variables

Two bivariate probit models with sample selection were specified. For the first model, the dependent variables representing Equations (5) and (6) were INFORMATION and VRFERTLIME (Table 1). INFORMATION equaled one if the farmer used at least one site-specific information technology listed in the survey and zero otherwise, while VRFERTLIME equaled one if the farmer used variable rate fertilizer and/or lime technology (hereafter variable rate fertilizer technology) given INFORMATION = 1 and zero otherwise. This model had 153 observations with INFORMATION = 1. Of these 153 observations, 79 had VRFERTLIME = 1 and 74 had VRFERTLIME = 0. Both dependent variables equaled zero for 620 observations. These observations, namely 79, 74, and 620, represented the numbers of farmers who had made the decisions corresponding to Equations (1) through (3)

with the probabilities expressed in Equations (7) through (9), respectively. The second model paired INFORMATION with VROTHER as dependent variables (Table 1), where VROTHER equaled one if the farmer used at least one of the other variable rate technologies (hereafter other variable rate technology) list in the survey (variable rate seed, growth regulator, defoliant, fungicide, herbicide, insecticide, irrigation) given INFORMATION = 1. This model had 31, 122, and 620 observations for farmers who had made the decisions corresponding to Equations (1) through (3).

Explanatory Variables

The aforementioned review of literature helped identify potential factors influencing technology adoption and develop hypotheses about their influence on the probability that a cotton farmer would adopt precision farming technologies. Data from the survey were used to develop proxy variables for the identified factors. Three explanatory variables represented characteristics of the farm (Table 1). Farm size (FARMSIZE) was expected to positively affect the probability of precision farming technology adoption by cotton farmers. A larger farm size allows fixed costs to be spread over more acres reducing the average cost of using these technologies. Also, larger farm size may be a proxy for a farmer's ability to bare the risk of adopting new technology. Land tenure can also affect adoption because a farmer is likely to manage owned land more intensely than rented land to preserve its productivity for future generations. Thus, the difference between the amounts of owned and rented land (OWNRENT) was hypothesized to have a positive effect on the probability of adopting precision farming technologies. High land quality represented by high farm-average cotton lint yield (YIELD) may indicate greater opportunities for spatial yield response variability; thus, YIELD was expected to have a positive influence on the probability of adopting precision farming technologies.

Three farmer characteristics were hypothesized to affect the probability that a farmer would adopt precision farming technologies (Table 1). The complexities of using precision farming technologies require considerable analytical ability, suggesting that farmers who have attended college (COLLEGE) may be more likely to possess the human capital to successfully evaluate and adopt precision farming technologies than those who have not attended college. Generally, older farmers have shorter planning horizons, diminished incentives to change, and less exposure to the technologies required for precision farming than younger farmers; thus, a farmer over 50 years old (OVER50) was hypothesized to be less likely to adopt precision farming technologies. Because computer technology is an integral part of precision farming, farmers who used a computer for farm management (COMPUTER) were expected to be more likely to adopt precision farming technologies than those who did not.

A farmer's knowledge and perceptions about the costs and potential benefits of precision farming were expected to influence adoption decisions (Table 1). A farmer who was less knowledgeable about these costs and potential benefits was hypothesized to be less likely to adopt precision farming technologies than one who was more knowledgeable. Inaccuracy in estimating the cost of purchasing a cotton yield monitoring system (PRICEDIFF) was used as a proxy for a farmer's lack of general knowledge about the costs and potential benefits of precision farming, and was hypothesized to have a negative relationship with the probability of adoption. The probability of adopting these technologies was expected to be higher for farmers who thought precision farming would be profitable for them to use in the future (PROFITABLE). Farmers who placed more importance on cotton precision farming in their state five years in the future (IMPORTANCE) were expected to have higher probabilities of adoption.

The variables AL, FL, GA, MS, and NC (Table 1) were included to test whether cotton farmers in Alabama, Florida, Georgia, Mississippi, and North Carolina had higher or lower probabilities of adopting precision farming technologies relative to cotton farmers in Tennessee.

The vectors of explanatory variables in Equations (5) and (6) (Z_s and Z_v) were identical in each model specification. Nothing in the specification of a bivariate probit model requires different regressors in the equations because the derivatives of the log likelihood function are not linearly dependent. Certainly, if ρ equals zero, the two equations can be estimated separately without regard to the contents of Z_s and Z_v (Greene, personal communication, February 18, 2003). Even though PRICEDIFF deals with a farmer's perceptions about the cost of a site-specific information technology (cotton yield monitoring), PRICEDIFF was included in both equations because it was considered a proxy for a farmer's lack of general knowledge about the costs and potential benefits of precision farming technology adoption.

Model Estimation

For each pair of dependent variables, Equations (5) and (6) were estimated with maximum likelihood methods as a bivariate probit model with sample selection, first with ρ constrained to zero and then unconstrained. A likelihood ratio test was performed to test the null hypothesis that ρ equals zero (Greene, 2003). Multicollinearity diagnostics were also performed (Belsley, Kuh, and Welsch).

Marginal effects were obtained by differentiating the probabilities in Equation (7) with respect to the explanatory variables. Three types of marginal effects were calculated by differentiating: 1) the marginal probability of adopting site-specific information technology, $\Pr(I_s = 1)$; 2) the conditional probability of adopting variable rate technology, $\Pr(I_v = 1 \mid I_s = 1)$; and 3) the joint probability of adopting both site-specific information and variable rate

technologies, $\Pr(I_s = 1; I_v = 1)$. The latter marginal effect can be viewed as the overall effect of a change in an explanatory variable on the probability of adopting variable rate technology because, if variable rate technology is adopted, it must be adopted jointly with site-specific information technology. This overall marginal effect has two components: 1) the variable's direct effect through its influence on the conditional probability of adopting variable rate technology given site-specific information technology adoption, and 2) the indirect effect through the variable's influence on the probability of adopting site-specific information technology, which in turn influences the probability of adopting variable rate technology.

Results

Estimated Models and Predictive Ability

Likelihood ratio tests indicated failure to reject the null hypothesis that ρ equals zero for each model specification. Separate binomial probit models for Equations (5) and (6) are presented in Table 2. The marginal effects in Table 2 are the marginal effects of the variables on $\Pr(I_s = 1)$ and $\Pr(I_v = 1 \mid I_s = 1)$, respectively. Chi-squared statistics indicate that the models significantly explained the adoption of site-specific information and variable rate technologies, although the conditional VROTHER model was statistically significant at the 10% level only. Multicollinearity diagnostics found that the standard errors of the coefficients were not seriously degraded. The INFORMATION model correctly predicted 80% of farmers' responses, while the conditional VRFERTLIME model and the conditional VROTHER model correctly predicted 71% and 78% of farmers' responses, respectively.

Site-Specific Information Technology Adoption

All marginal effects of the explanatory variables in the INFORMATION model had their hypothesized signs (Table 2). Farm size (FARMSIZE), land quality (YIELD), college attendance (COLLEGE), farmer age (OVER50), farmer perceptions about the future profitability of precision farming on their farm (PROFITABLE) and the future importance of

cotton precision farming in their state (IMPORTANCE), and the dummy variable for farms located in Alabama (AL) affected the probability that a cotton farmer would adopt site-specific information technology. Land tenure (OWNRENT), computer use for farm management (COMPUTER), and lack of general knowledge about the costs and potential benefits of precision farming (PRICEDIFF) were not related to the probability that a cotton farmer would adopt site-specific information technology.

Variable Rate Fertilizer Technology Adoption

The conditional probability of adopting variable rate fertilizer technology (VRFERTLIME) given INFORMATION =1 was significantly related to land tenure (OWNRENT), farmer age (OVER50), lack of general knowledge about the costs and potential benefits of precision farming (PRICEDIFF), and dummy variables for farms located in Alabama (AL), Georgia (GA), and North Carolina (NC) (Table 2). Farm size (FARMSIZE), land quality (YIELD), college attendance (COLLEGE), computer use for farm management (COMPUTER), and optimism about the future of precision farming (PROFITABLE and IMPORTANCE) did not affect the conditional probability of adopting variable rate fertilizer technology.

Several important conclusions can be drawn from considering the overall marginal effects on the probability of adopting variable rate fertilizer technology (VRFERTLIME) in Table 3 in relation to the marginal effects in Table 2. Farmer age (OVER50) had statistically significant marginal effects in common among the marginal effects in Tables 2 and 3. Clearly, older farmers were less likely to adopt site-specific information technology than younger farmers, but given that they had adopted site-specific information technology, they were even less likely to adopt variable rate fertilizer technology than younger farmers (Table 2). The indirect effect of age through adoption of site-specific information technology and the direct effect of age (given adoption of site-specific information technology) worked

together to give a highly statistically significant negative overall marginal effect for OVER50 (Table 3).

Land quality (YIELD) had a statistically significant positive marginal effect in the INFORMATION model and a negative marginal effect in the conditional VRFERTLIME model (although significant at $\alpha = 13\%$ only), but did not have a statistically significant overall marginal effect on the probability of adopting variable rate fertilizer technology (Table 3). The unexpected negative marginal effect for YIELD in the conditional VRFERTLIME model and the positive marginal effect for YIELD in the INFORMATION model in Table 2 suggest that farmers with higher quality land may have anticipated greater potential benefits from adopting site-specific information technology (mostly precision soil sampling technology) than farmers with lower quality land; but after evaluating the site-specific information (mostly soil test information) they may have discovered that high average lint yield did not necessarily translate into high spatial variability in fertilizer or lime application prescriptions. These opposite indirect and direct effects combined to offset each other; thus, land quality as measured by farm-average cotton lint yield was not related to the probability of adopting variable rate fertilizer technology.

Farm size (FARMSIZE) and farmer perceptions about the future profitability of precision farming on their farm (PROFITABLE) and the future importance of cotton precision farming in their state (IMPORTANCE) were statistically related to the probability of adopting variable rate fertilizer technology mostly through their indirect effects on the probability of adopting site-specific information technology. The marginal effects of these variables in the INFORMATION model (Table 2) and their overall marginal effects (Table 3) were statistically significant, but their marginal effects were not statistically significant in the conditional VRFERTLIME model (Table 2). Thus, these variables affected the probability of

adopting variable rate fertilizer technology by stimulating farmers to get started in precision farming by gathering site-specific information.

Land tenure (OWNRENT) and lack of general knowledge about the costs and potential benefits of precision farming (PRICEDIFF) affected the probability of variable rate fertilizer technology adoption mostly through their direct effects on the conditional probability of adoption. The marginal effects of these variables in the conditional VRFERTLIME model (Table 2) and their overall marginal effects (Table 3) were statistically significant, but their marginal effects were not statistically significant in the INFORMATION model (Table 2). This finding for OWNRENT suggests that farmers who had already gathered site-specific information viewed the difference between the perceived long-term benefits and costs of variable rate fertilizer or lime application more positively on owned land than on rented land. This finding for PRICEDIFF suggests that farmers who had already gathered site-specific information were less likely to take the next step in the sequential technology adoption process if they lacked general knowledge about the costs and potential benefits of variable rate fertilizer or lime application.

Conditional and overall marginal effects on the probability of adopting variable rate fertilizer technology in Tables 2 and 3 were not statistically significant for college attendance (COLLEGE), but COLLEGE significantly affected the probability of adopting site-specific information technology (Table 2). The statistically significant positive effect of college attendance in the INFORMATION model was mollified by the nonsignificant effect of college attendance in the conditional VRFERTLIME model. The unexpected negative coefficient for COLLEGE in the conditional model, although statistically nonsignificant, contributed to this mollification. Results suggest that farmers who had attended college were more likely to gather site-specific information than less educated farmers, but given the site-

specific information, college attendance was not related to the variable rate versus uniform rate fertilizer application decision.

Other Variable Rate Technology Adoption

The probability of adopting other variable rate technology (VROTHER) given INFORMATION = 1 was only related to the state in which the farm was located (Table 2); Alabama (AL) and Georgia (GA) farmers were more likely to adopt other variable rate technology for cotton production than Tennessee farmers. The marginal effect for COLLEGE was not statistically significant in the conditional VROTHER model, whereas its marginal effect was significant in the INFORMATION model (Table 2). The net result was that COLLEGE had a statistically significant overall marginal effect on the probability of adopting other variable rate technology (Table 3). This result suggests that college attendance was positively related to the probability that a cotton farmer would adopt site-specific information technology, which indirectly increased the probability of adopting variable rate application of seed, growth regulator, defoliant, fungicide, herbicide, insecticide, and/or irrigation.

Several variables that had statistically significant marginal effects in the INFORMATION model (Table 2) did not have significant overall marginal effects on the probability of adopting other variable rate technology (Table 3). The statistically nonsignificant marginal effects in the conditional VROTHER model diluted the significant effects of these variables in the INFORMATION model (Table 2). For example, FARMSIZE and OVER50 had unexpected signs in the conditional VROTHER model. Although these direct effects were not statistically significant, the net result of their unexpected signs was to counteract the indirect effects of these variables to give statistically nonsignificant overall marginal effects on the probability of adopting other variable rate technology (Table 3).

Summary and Conclusions

Farmers were assumed to maximize expected utility from making decisions about the adoption of precision farming technologies. Because site-specific information about a field is required to create prescriptions for variable rate input application, farmers adopt site-specific information technology before adopting variable rate input application technology. Thus, a sequential adoption process was assumed and probit methods with sample selection were used to identify farm and farmer characteristics that influenced the probability that cotton farmers would adopt these technologies in six Southeastern states.

Results suggest that younger, more educated cotton farmers who operate larger farms and are optimistic about the future profitability and importance of precision farming are more likely to adopt site-specific information technologies than other farmers. By targeting efforts toward these farmers, agribusiness firms and extension personnel can increase their probabilities of success in reaching cotton farmers who are most likely to purchase site-specific information technologies and benefit from extension education programs.

Alternatively, targeting cotton farmers who use computers for farm management and those who are well informed about the costs and potential benefits of precision farming may not increase the probability of successful site-specific information technology adoption. These characteristics may not be important in influencing the probability of adoption because most responding farmers who adopted site-specific information technology had adopted precision soil sampling technology (136 of 153 farmers, 89%), and precision soil sampling technology is typically custom hired, shifting much of the burden of knowledge and computer expertise to the agribusiness firm.

Results also suggest that targeting younger cotton farmers who operate larger farms, own more of the land they farm, are more informed about the costs and potential benefits of precision farming, and are more optimistic about the future profitability and importance of

precision farming than other farmers will: 1) help agribusiness firms promote sales of their variable rate fertilizer technology products, and 2) help extension personnel target cotton farmers who will most likely benefit from their variable rate fertilizer technology education programs. Directing efforts toward cotton farmers with high quality land who have attended college and have used a computer for farm management does not appear to increase the probability of variable rate fertilizer technology adoption.

Targeting farmers with knowledge about the costs and potential benefits of precision farming is more important for variable rate fertilizer technology adoption than for site-specific information technology adoption because variable rate versus uniform rate application decisions are the farmer's responsibility once the site-specific information has been gathered. Like site-specific information technology, variable rate fertilizer technology is typically custom-hired, many times from the same firm that gathers the site-specific information. A more informed farmer will likely interpret the site-specific information more accurately than a less informed farmer, and before making the utility-maximizing variable rate versus uniform rate decision, pass the agribusiness firm's recommendations through a filter of greater knowledge and certainty.

For agribusiness firms and extension personnel interested in other variable rate technology (i.e., variable rate application of seed, growth regulator, defoliant, fungicide, herbicide, insecticide, or irrigation), targeting cotton farmers who have attended college appears to be a promising alternative for increasing the probability of successful promotional efforts and extension programs.

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Table 1. Definitions of Dependent and Explanatory Variables Used in the Probit Regressions

Variable	Mean	Sign	Definition
Dependent Variables			
INFORMATION	0.20	^a	Used at least one site-specific information technology (yes=1; no=0)
VRFERTLIME	0.10	^a	Used variable rate fertilizer and/or lime technology (yes=1; no=0)
VROTHER ^b	0.04	^a	Used at least one other variable rate input technology (yes=1; no=0)
Explanatory Variables			
Farm Characteristics			
FARMSIZE	0.74	+	Farm acreage (1000 acres)
OWNRENT	-0.40	+	Acres owned minus acres rented (1000 acres)
YIELD	0.67	+	Farm-average lint yield in 2000 (1000 lb/acre)
Farmer Characteristics			
COLLEGE	0.64	+	Attended some college (yes=1; no=0)
OVER50	0.41	–	Was over 50 years old (yes=1; no=0)
COMPUTER	0.52	+	Used a computer for farm management (yes=1; no=0)
Farmer Perceptions			
PRICEDIFF ^c	0.22	–	Absolute value of the difference between the farmer's perception of the cost of a cotton yield monitoring system and the actual cost of a cotton yield monitoring system was over \$3,000 (yes=1; no=0)
PROFITABLE	0.72	+	Farmer thought precision farming technologies would be profitable for him/her to use in the future (yes=1; no=0)
IMPORTANCE	3.6	+	Farmer thought cotton precision farming would be unimportant (1) to very important (5) in his/her state five years in the future
Farm Location			
AL	0.15	+ –	Farm in Alabama (yes=1; no=0)
FL	0.05	+ –	Farm in Florida (yes=1; no=0)
GA	0.14	+ –	Farm in Georgia (yes=1; no=0)
MS	0.25	+ –	Farm in Mississippi (yes=1; no=0)
NC	0.27	+ –	Farm in North Carolina (yes=1; no=0)

^a Not applicable.^b Variable rate application of seed, growth regulator, defoliant, fungicide, herbicide, insecticide, or irrigation.^c The actual cost of a cotton yield monitoring system at the time of the survey was \$9,500. PRICEDIFF was assigned a value of 0 for farmers who did not answer this survey question. This assignment was made based on the assumption that these farmers were less informed about the costs and potential benefits of precision farming than those who gave an answer within \$3,000 of the actual cost.

Table 2. Estimated Binomial Probit Models for Site-specific Information Gathering Technology and Conditional Variable Rate Fertilizer and Other Variable Rate Technologies

Explanatory Variable ^a	INFORMATION		VRFERTLIME Given INFORMATION = 1		VROTHER Given INFORMATION = 1	
	Coefficient	Marginal Effect ^b	Coefficient	Marginal Effect ^c	Coefficient	Marginal Effect ^c
CONSTANT	-2.388***		-0.349		-2.727***	
FARMSIZE	0.133**	0.034**	0.104	0.041	-0.161	-0.041
OWNRENT	0.020	0.005	0.186*	0.074*	-0.049	-0.012
YIELD	0.445*	0.114*	-0.893	-0.356	0.729	0.186
COLLEGE	0.386***	0.099***	-0.122	-0.049	0.475	0.121
OVER50	-0.319***	-0.081***	-0.538**	-0.214**	0.229	0.058
COMPUTER	0.104	0.026	0.040	0.016	0.086	0.022
PRICEDIFF	-0.181	-0.046	-0.580**	-0.231**	-0.363	-0.093
PROFITABLE	0.351**	0.090**	0.269	0.107	0.351	0.089
IMPORTANCE	0.129**	0.033**	0.128	0.051	0.089	0.023
AL	0.518**	0.132**	0.862*	0.343*	0.985***	0.251***
FL	0.140	0.036	0.690	0.275	d	d
GA	0.340	0.087	0.767*	0.305*	0.824**	0.210**
MS	0.105	0.027	0.367	0.146	d	d
NC	0.191	0.049	0.722*	0.287*	d	d
n	773		153		153	
Correctly Pred.	621 (80%)		109 (71%)		120 (78%)	
χ^2 with 14 df	71.613***		28.941**		17.318* ^e	

^a Variables are defined in Table 1.

^b Marginal effects indicate the change in the probability of adopting site-specific information technology for a change in an explanatory variable.

^c Marginal effects indicate the change in the conditional probability of adopting the technology, given site-specific information technology adoption, for a change in an explanatory variable.

^d Too few observations in these states.

^e Chi-squared with 11 degrees of freedom.

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

Table 3. Estimated Overall Marginal Effects of the Explanatory Variables on the Probability of Variable Rate Technology Adoption

Explanatory Variable ^b	Overall Marginal Effects ^a	
	VRFERTLIME	VROTHER
FARMSIZE	0.022 [*]	-0.002
OWNRENT	0.015 [*]	-0.001
YIELD	-0.010	0.043
COLLEGE	0.035	0.030 ^{**}
OVER50	-0.073 ^{***}	-0.002
COMPUTER	0.014	-0.001
PRICEDIFF	-0.060 ^{**}	-0.019
PROFITABLE	0.058 [*]	0.089
IMPORTANCE	0.023 [*]	0.023
AL	0.117 ^{***}	0.049 ^{***}
FL	0.063	c
GA	0.091 ^{**}	0.037 ^{**}
MS	0.037	c
NC	0.071	c

^a Variables are defined in Table 1.

^b Marginal effects indicate the change in the joint probability of adopting both variable rate and site-specific information technologies for a change in an explanatory variable.

^c Too few observations in these states.

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