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Adoption of Site-Specific Information and Variable-Rate Technologies in Cotton Precision Farming

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Probit analysis identified factors that influence the 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.

Key Words: cotton, grid soil sampling, precision farming, probit, sample selection, site-specific information, technology adoption, variable-rate application

JEL Classifications: D21, Q12, Q16

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 the 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 the analysis of technol-

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ogy 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 (1) discussed or evaluated factors influencing adoption using survey results (Arnholt, Batte, and Prochaska; Batte and Arnholt; Daberkow, Fernandez-Cornejo, and Padgitt, 2002a; Daberkow and McBride; 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; Isik, Khanna, and Winter-Nelson; Jaenicke and Cohen-Vogel), 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). Whereas Khanna's research evaluated the adoption of soil testing (not necessarily site-specific soil testing) and the 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 to 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.

The analytical framework is presented first, followed by the data used in the analysis. The empirical model is discussed along with the hypothesized relationships between technology adoption decisions and factors that might affect those decisions. Results and conclusions are then presented.

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. Furthermore, 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) $U_s^* = Z_s\gamma_s + \varepsilon_s, \qquad U_v^* = Z_v\gamma_v + \varepsilon_v,$

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,

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

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

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

$$\begin{aligned}
(7)\quad & \Pr(I_s = 1; I_v = 1) \\
& = \Pr(I_v = 1 \mid I_s = 1) \times \Pr(I_s = 1) \\
& = \Phi_2(Z_s\gamma_s, Z_v\gamma_v, \rho), \\
(8)\quad & \Pr(I_s = 1; I_v = 0) \\
& = \Phi(Z_s\gamma_s) - \Pr(I_s = 1; I_v = 1) \\
& = \Phi_2(Z_s\gamma_s, -Z_v\gamma_v, -\rho), \\
(9)\quad & \Pr(I_s = 0) = 1 - \Phi(Z_s\gamma_s) = \Phi(-Z_s\gamma_s),
\end{aligned}$$

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. The probabilities in Equations (7)–(9) enter the sample likelihood function as

$$\begin{aligned}
(10)\quad L = & \prod_{I_s=1, I_v=1} \Phi_2(Z_s\gamma_s, Z_v\gamma_v, \rho) \\
& \times \prod_{I_s=1, I_v=0} \Phi_2\,(Z_s\gamma_s, -Z_v\gamma_v, -\rho) \\
& \times \prod_{I_s=0} \Phi(-Z_s\gamma_s).
\end{aligned}$$

If $\rho = 0$, the bivariate distribution reduces to the product of two univariate distributions and the likelihood function becomes,

$$\begin{aligned}
(11)\quad L = & \prod_{I_s=1, I_v=1} \Phi(Z_s\gamma_s)\Phi(Z_v\gamma_v) \\
& \times \prod_{I_s=1, I_v=0} \Phi(Z_s\gamma_s)\Phi(-Z_v\gamma_v) \prod_{I_s=0} \Phi(-Z_s\gamma_s) \\
= & \prod_{I_s=1} \Phi(Z_s\gamma_s) \prod_{I_s=0} \Phi(-Z_s\gamma_s) \prod_{I_s=1, I_v=1} \Phi(Z_v\gamma_v) \\
& \times \prod_{I_s=1, I_v=0} \Phi(-Z_v\gamma_v).
\end{aligned}$$

The log-likelihood function for Equation (5) is the logarithm of the first two terms of Equation (11), whereas the log-likelihood function for Equation (6) is the logarithm of the last two terms of Equation (11). 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 subsample of farmers eligible to make the VRT versus URT decision ($I_s = 1$ only). These log-likelihood functions can be maximized separately because the logarithm of Equation (11) is separable in the parameter vectors γ_s and γ_v, making the Hessian block diagonal.

Data

Data were collected from a mail survey of cotton farmers in Alabama, Florida, Georgia, Mississippi, North Carolina, and Tennessee conducted in 2001 (Roberts et al.). The Cotton Board in Memphis, Tennessee, provided the list of potential cotton farmers for the 1999–2000 crop season (Skorupa). The survey questionnaire was pretested on two Tennessee farmers, and their suggestions were incorporated into the final version. 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 mailed on January 16, 2001, and a reminder postcard was sent 1 week later, on January 23, 2001. A follow-up mailing to producers not responding to previous inquiries was conducted 3 weeks later on February 15, 2001. The second mailing included a letter indicating the importance of the survey, the questionnaire, and a postage-paid return envelope.

Of the 6,423 questionnaires mailed, 196 were returned as undeliverable and 251 respondents indicated that they were not cotton farmers or they had retired, leaving 5,976 cotton farmers who received the questionnaire. A total of 1,131 (19%) cotton farmers 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. For example, the 24 satellites in the GPS system were launched between 1989 and 1994 (Aerospace Corporation) and became available for variable-rate input application in the early 1990s, and cotton yield monitors first became commercially available in 1997 (Durrence et al.; Roades, Beck, and Searcy). 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 the present 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 5 years or (2) variable-rate nitrogen, phosphorous and potassium, or lime application for more than 9 years Observations for three respondents were eliminated for reporting that they had used yield monitoring technology for more than 5 years, and another 13 respondents were eliminated for reporting that they had used variable-rate fertilizer and/or lime technology for more than 9 years.

Reducing the sample size from 1,131 to 773 did not significantly affect sample means (see means in Table 1), lending credence to the results from the reduced sample. For example, the proportion of respondents who had attended college was 0.64 in the reduced sample, compared with 0.56 in the original sample; the proportions who had used a computer for farm management were 0.52 and 0.60 for the reduced and original samples, respectively; sample differences in average farm size and average lint yield were only 10 acres and 10 lb./acres, respectively; and the proportion of farmers over age 50 years of age was 0.41 in both samples.

Empirical Model

Dependent Variables

The data provided opportunities to specify three bivariate probit models with sample selection. Estimation procedures failed for other models because of small numbers of adopters relative to nonadopters. 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, and *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)–(3) with the probabilities expressed in Equations (7)–(9), respectively.

The second bivariate probit model was specified with *SOILSAMPLE* and *VRFERTLIME* as the dependent variables (Table 1).

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

Variable	Mean[a]	Sign	Definition
Dependent Variables			
Site-Specific Information			
INFORMATION	0.20 (0.19)	[b]	Used at least one site-specific information technology (yes = 1; no = 0)
SOILSAMPLE	0.18 (0.17)	[b]	Used grid and/or management zone soil-sampling technology (yes = 1; no = 0)
Variable Rate			
VRFERTLIME	0.10 (0.12)	[b]	Used variable-rate fertilizer and/or lime technology (yes = 1; no = 0)
VROTHER[c]	0.04 (0.07)	[b]	Used at least one other variable-rate input technology (yes = 1; no = 0)
Explanatory Variables			
Farm Characteristics			
FARMSIZE	0.74 (0.75)	+	Farm acreage (1,000 acres)
OWNRENT	−0.40 (−0.31)	+	Acres owned minus acres rented (1,000 acres)
YIELD	0.67 (0.68)	+	Farm-average lint yield in 2000 (1,000 lb/acre)
Farmer Characteristics			
COLLEGE	0.64 (0.56)	+	Attended some college (yes = 1; no = 0)
OVER50	0.41 (0.41)	−	Was over 50 years old (yes = 1; no = 0)
COMPUTER	0.52 (0.60)	+	Used a computer for farm management (yes = 1; no = 0)
Farmer Perceptions			
PRICEDIFF[d]	0.22 (0.18)	−	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 (0.69)	+	Farmer thought precision farming technologies would be profitable for him/her to use in the future (yes = 1; no = 0)
IMPORTANCE	3.6 (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 (0.21)	+−	Farm in Alabama (yes = 1; no = 0)
FL	0.05 (0.04)	+−	Farm in Florida (yes = 1; no = 0)
GA	0.14 (0.13)	+−	Farm in Georgia (yes = 1; no = 0)
MS	0.25 (0.23)	+−	Farm in Mississippi (yes = 1; no = 0)
NC	0.27 (0.26)	+−	Farm in North Carolina (yes = 1; no = 0)

[a] Numbers in parentheses are means from the original sample of 1,131 respondents. *ACREAGE, OWNRENT, YIELD, COMPUTER, PROFITABLE,* and *IMPORTANCE* had fewer than 1,131 observations because of missing data.
[b] Not applicable.
[c] Variable-rate application of seed, growth regulator, defoliant, fungicide, herbicide, insecticide, or irrigation.
[d] The actual cost of a cotton yield monitoring system at the time of the survey was $9,500. *PRICEDIFF* was used as a proxy for a farmer's lack of general knowledge and awareness about the costs and potential benefits of precision farming. *PRICEDIFF* was assigned a value of 0 for farmers who did not answer this survey question. This assignment was made on the basis of 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.

SOILSAMPLE equaled one if the farmer used grid and/or management zone soil sampling technology (hereafter precision soil sampling technology) and zero otherwise, and *VRFERTLIME* equaled one if the farmer used variable-rate fertilizer technology given *SOILSAMPLE* = 1 and zero otherwise. This model had 136 observations with *SOILSAMPLE* = 1, and 76, 60, and 637 observations corresponding to farmers who had chosen the alternatives in Equations (1)–(3), respectively.

The third 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 VRT) list in the survey (variable-rate seed, growth regulator, defoliant, fungicide, herbicide, insecticide, and irrigation) given *INFORMATION* = 1. This model had 31, 122, and 620 observations for farmers who had made the decisions corresponding to Equations (1)–(3).

The two site-specific information technology variables were not mutually exclusive, nor were the two variable-rate input application technology variables. *INFORMATION* and *SOILSAMPLE* were not mutually exclusive, because the 136 respondents with *SOILSAMPLE* = 1 were a subset of the 153 respondents with *INFORMATION* = 1. Thus, only 17 respondents (153 − 136) had not adopted precision soil-sampling technology but had adopted at least one of the other site-specific information technologies listed in the survey. This number of adopters was too small for successful maximum likelihood estimation; therefore, *INFORMATION* and *SOILSAMPLE* were paired with *VRFERTLIME* in separate bivariate probit models as described above to see if results would be different between the models. *VRFERTLIME* and *VROTHER* were not mutually exclusive because 21 farmers reported using VRTs in both categories. Thus, *VRFERTLIME* and *VROTHER* were paired with *INFORMATION* to determine whether farmers who had adopted other VRT were different from those who had adopted variable-rate fertilizer technology, regardless of whether they had adopted the former, the latter, or both. Pairing *SOILSAMPLE* with *VROTHER* was not considered because precision soil sampling technology is mostly used to create variable-rate application maps for fertilizer and lime and less for other inputs.

Explanatory Variables

The aforementioned review of literature helped to identify potential factors influencing technology adoption and to 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 bear the risk of adopting a 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, which suggests 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 5 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. Each state had extension personnel actively working with farmers on precision farming issues and held field days when precision farming information was presented to farmers. In addition, agribusiness firms were actively promoting precision farming and sales of their precision farming equipment and services. Thus, the signs of the location variables could not be hypothesized *a priori*, and speculation on reasons for differences among states was difficult. Nevertheless, the survey data allowed differences to be estimated if they existed.

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 $\rho = 0$, 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 to be 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 (Greene 1998b), first with ρ constrained to zero and then unconstrained. A likelihood-ratio test was performed to test the null hypothesis that $\rho = 0$ (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 a variable-rate technology because, if a variable-rate technology is

Table 2. Log-Likelihood Ratio Tests of the Null Hypothesis that ρ Equals Zero

Bivariate Probit Model[a]	Log Likelihood		Likelihood Ratio Statistic[b]
	ρ Restricted to 0	ρ Unrestricted	
INFORMATION and *VRFERTLIME*	−440.28	−440.25	0.06
INFORMATION and *VROTHER*	−417.71	−417.66	0.11
SOILSAMPLE and *VRFERTLIME*	−405.32	−405.29	0.05

[a] Variables are defined in Table 1.

[b] The Likelihood Ratio Statistic is LR = −2(log likelihood ρ restricted − log likelihood ρ unrestricted). The critical value for chi-square with 1 degree of freedom at the 5% significance level is 3.84 (Greene, 2003).

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. Standard errors for all marginal effects were estimated using the delta method (Greene 1998a).

Results

Estimated Models and Predictive Ability

Likelihood-ratio tests indicated failure to reject the null hypothesis that $\rho = 0$ for each model specification (Table 2). Separate binomial probit models for Equations (5) and (6) are presented in Tables 3 and 4, respectively. The marginal effects presented in Tables 3 and 4 are the marginal effects of changes in the variables on $\Pr(I_s = 1)$ and $\Pr(I_v = 1 \mid I_s = 1)$, respectively. χ^2 statistics indicated that the models significantly explained the adoption of site-specific informaton and variable-rate technologies, although the conditional *VROTHER* model in Table 4 was statistically significant only at the 10% level. The *INFORMATION* and *SOILSAMPLE* models in Table 3 correctly predicted 80% and 83% of farmers' responses, whereas the conditional *VRFERTLIME* models and the conditional *VROTHER* model in Table 4 correctly predicted 71%, 69%, and 78% of farmers' responses, respectively.

Model predictions for the choices expressed in Equations (1)–(3) are presented in Table 5. With regard to the 153 cotton farmers who adopted at least one site-specific information technology, the conditional model for *VRFERTLIME* given *INFORMATION* = 1 in Table 4 correctly predicted 77% of farmers who also adopted variable-rate fertilizer technology and 65% of the farmers who chose not to adopt variable-rate fertilizer technology. The conditional *VROTHER* model given *INFORMATION* = 1 performed poorly in predicting farmers who also adopted other VRT (3%) but did well in predicting those farmers who chose not to adopt other VRT (98%). The *INFORMATION* model in Table 3 correctly predicted 99% of cotton farmers who chose not to adopt any precision farming technologies.

For the 136 farmers who adopted precision soil-sampling technology, the conditional model for *VRFERTLIME* given *SOILSAMPLE* = 1 in Table 4 correctly predicted 78% of farmers who also adopted variable-rate fertilizer technology and 58% of farmers who chose not to adopt variable-rate fertilizer technology. In addition, the *SOILSAMPLE* model in Table 3 correctly predicted 99% of cotton farmers who chose not to adopt precision soil sampling or variable-rate fertilizer technologies.

Multicollinearity Diagnostics

The reliability of the test statistics used to determine significance of the coefficients and marginal effects in Tables 3 and 4 could be questioned if the standard errors were seriously degraded by multicollinearity. Multicollinearity diagnostics found that the standard er-

Table 3. Estimated Binomial Probit Models for Site-Specific Information Technologies and Marginal Effects of the Explanatory Variables on the Marginal Probability of Site-Specific Information Technology Adoption

	INFORMATION		SOILSAMPLE	
Explanatory Variable[a]	Coefficient	Marginal Effect[b]	Coefficient	Marginal Effect[b]
CONSTANT	−2.388***		−2.418***	
FARMSIZE	0.133**	0.034**	0.112*	0.026*
OWNRENT	0.020	0.005	0.047	0.011
YIELD	0.445*	0.114*	0.474*	0.110*
COLLEGE	0.386***	0.099***	0.298**	0.069**
OVER50	−0.319***	−0.081***	−0.346***	−0.080***
COMPUTER	0.104	0.026	0.042	0.010
PRICEDIFF	−0.181	−0.046	−0.218	−0.051
PROFITABLE	0.351**	0.090**	0.424**	0.098**
IMPORTANCE	0.129**	0.033**	0.154**	0.036**
AL	0.518**	0.132**	0.460**	0.107**
FL	0.140	0.036	0.111	0.026
GA	0.340	0.087	0.245	0.057
MS	0.105	0.027	−0.024	−0.006
NC	0.191	0.049	0.061	0.014
n	773		773	
Correctly Predicted	621 (80%)		638 (83%)	
χ^2 14 df	71.613***		71.072***	

[a] Variables are defined in Table 1.
[b] Marginal effects indicate the change in the marginal probability of adopting the technology for a change in an explanatory variable.
Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

rors were not seriously degraded. The largest condition index for the equations in Table 3 was 16.7, which is below the lower threshold of 20 suggested by Belsley, Kuh, and Welsch. For the equations in Table 4, the largest condition indexes were 20.5 for the conditional *VRFERTLIME* and *VROTHER* models (given *INFORMATION* = 1) and 20.9 for the conditional *VRFERTLIME* model (given *SOILSAMPLE* = 1), which were close to the lower threshold, suggesting the possibility of weak linear dependency among the explanatory variables. However, no linear dependences were identified because two or more explanatory variables did not have variance proportions greater than 0.5.

Site-Specific Information Technology Adoption

All marginal effects of the explanatory variables in the *INFORMATION* and *SOILSAMPLE* models had their hypothesized signs (Table 3) and the explanatory variables had statistically significant marginal effects of about the same magnitudes in each model. Thus, the results were not appreciably different between farmers who adopted precision soil sampling technology and those who adopted other site-specific information technology but not precision soil sampling technology.

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 a

Table 4. Estimated Conditional Binomial Probit Models for Variable-Rate Input Application Technologies and Marginal Effects of the Explanatory Variables on the Conditional Probability of Variable-Rate Technology Adoption

	VRFERTLIME Given *INFORMATION* = 1		*VRFERTLIME* Given *SOILSAMPLE* = 1		*VROTHER* Given *INFORMATION* = 1	
Explanatory Variable[a]	Coefficient	Marginal Effect[b]	Coefficient	Marginal Effect[b]	Coefficient	Marginal Effect[b]
CONSTANT	−0.349		−0.348		−2.727***	
FARMSIZE	0.104	0.041	0.099	0.039	−0.161	−0.041
OWNRENT	0.186*	0.074*	0.139	0.055	−0.049	−0.012
YIELD	−0.893	−0.356	−1.041*	−0.408*	0.729	0.186
COLLEGE	−0.122	−0.049	−0.088	−0.034	0.475	0.121
OVER50	−0.538**	−0.214**	−0.591**	−0.232**	0.229	0.058
COMPUTER	0.040	0.016	0.023	0.009	0.086	0.022
PRICEDIFF	−0.580**	−0.231**	−0.497*	−0.195*	−0.363	−0.093
PROFITABLE	0.269	0.107	0.307	0.120	0.351	0.089
IMPORTANCE	0.128	0.051	0.124	0.048	0.089	0.023
AL	0.862*	0.343*	0.996**	0.391**	0.985***	0.251***
FL	0.690	0.275	0.765	0.300	[c]	[c]
GA	0.767*	0.305*	0.872*	0.342*	0.824**	0.210**
MS	0.367	0.146	0.566	0.222	[c]	[c]
NC	0.722*	0.287*	0.877*	0.344*	[c]	[c]
n	153		136		153	
Correctly Predicted	109 (71%)		94 (69%)		120 (78%)	
χ^2 14 df	28.941**		24.112**		17.318*[d]	

[a] Variables are defined in Table 1.

[b] 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.

[c] Too few observations.

[d] χ^2 with 11 degrees of freedom.

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

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.

These results were different from those found in Khanna's study of precision farming technology adoption in four Midwestern states. She found that soil quality, proximity to a fertilizer dealer, and whether the farmer had forward contracts based on product quality were significant variables relating to the probability of soil test adoption. Farm size, college attendance, and farmer experience (correlated with farmer age), which were significant in our study, were not significant variables in her study. The positive sign for the marginal effect of soil (land) quality on the probability of adoption was the only similarity between the studies. Results differed because of differences in the data used for the analyses. First, Khanna's study dealt with farmers in the Midwest producing mostly grains and oil seeds, whereas ours dealt with cotton farmers in the Southeast. Second, she used data from a survey about adoption decisions in 1996, whereas our survey asked about adoption decisions 4 years later, in 2000. Third, the dependent variable in her study indicated whether the farmer had adopted one or more soil fertility tests (Khanna, pp. 40–41), "such as late spring test, pre-sidedress test, plant tissue test, soil test, and grid soil sampling," which are not necessarily used to identify variation in soil fertility within a field. The data we used were expressly related to the adoption of precision soil sampling and other site-specific information technologies. Last, in several in-

Table 5. Model Predictions Compared with Actual Numbers of Cotton Farmers Adopting Precision Farming Technologies

Model[a]	Adopters of Site-Specific Information and Variable-Rate Technologies[b]	Adopters of Site-Specific Information Technologies Only[b]	Nonadopters of Precision Farming Technologies[c]
INFORMATION and *VRFERTLIME*			
Predicted	61	48	615
Actual	79	74	620
Correctly Predicted (%)	77	65	99
INFORMATION and *VROTHER*			
Predicted	1	119	615
Actual	31	122	620
Correctly Predicted (%)	3	98	99
SOILSAMPLE and *VRFERTLIME*			
Predicted	59	35	633
Actual	76	60	637
Correctly Predicted (%)	78	58	99

[a] Variables are defined in Table 1.

[b] Predicted numbers in these columns are from the conditional variable-rate technology models in Table 4.

[c] Predicted numbers in this column are from the site-specific information technology models in Table 3.

stances, the explanatory variables were different between the studies. For example, Khanna included a variable for distance from a fertilizer dealer, whereas we included *PRICEDIFF* as a proxy for a farmer's lack of general knowledge about the costs and potential benefits of precision farming.

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 (OVERR50), 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 4). The conditional probability of variable-rate fertilizer technology adoption given *SOILSAMPLE* = 1 was affected by almost the same variables, except that land quality (*YIELD*) affected the conditional probability of adoption and land tenure (*OWNRENT*) did not. This difference in results between the two models was not large. The signs of *YIELD* and *OWNRENT* were the same in both models, and *YIELD* was significant at the 13% level in the conditional model for *VRFERTLIME,* given the *INFORMATION* = 1, and *OWNRENT* was significant at the 14% level in the conditional model for *VRFERTLIME,* given the *SOILSAMPLE* = 1.

The results for the conditional *VRFERTLIME* models suggested that similar factors affected the probability of adopting variable-rate fertilizer technology, regardless of whether the farmer had adopted precision soil sampling technology or some other site-specific information technology (e.g., satellite imagery) for use in creating the variable-rate fertilizer or lime application map. Similarities between the overall marginal effects for *VRFERTLIME* and *INFORMATION* and the overall marginal effects for *VRFERTLIME* and *SOILSAMPLE* in Table 6 provide further evidence that the *INFORMATION* and *SOILSAMPLE* models, conditional or otherwise, are about the same. Consequently, for ease of exposition and to avoid repetition, the discussion that follows re-

Table 6. Estimated Overall Marginal Effects of the Explanatory Variables on the Probability of Variable-Rate Technology Adoption

Explanatory Variable[b]	Overall Marginal Effects[a]		
	VRFERTLIME and *INFORMATION*	*VRFERTLIME* and *SOILSAMPLE*	*VROTHER* and *INFORMATION*
FARMSIZE	0.022*	0.018*	−0.002
OWNRENT	0.015*	0.013*	−0.001
YIELD	−0.010	−0.010	0.043
COLLEGE	0.035	0.027	0.030**
OVER50	−0.073***	−0.073***	−0.002
COMPUTER	0.014	0.006	−0.001
PRICEDIFF	−0.060**	−0.053**	−0.019
PROFITABLE	0.058*	0.065*	0.089
IMPORTANCE	0.023*	0.024**	0.023
AL	0.117***	0.109***	0.049***
FL	0.063	0.058	[c]
GA	0.091**	0.079*	0.037**
MS	0.037	0.031	[c]
NC	0.071	0.059	[c]

[a] Variables are defined in Table 1.

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

[c] Too few observations.

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

fers to both models in Table 3 as the *INFORMATION* model, it refers to both conditional *VRFERTLIME* models in Table 4 as the conditional *VRFERTLIME* model, and it refers the to the two overall marginal effects for *VRFERTLIME* in Table 6 as the overall marginal effects on the probability of adopting variable-rate fertilizer technology.

Results for the conditional *VRFERTLIME* model in Table 4 were different from those found by Khanna. As with the *INFORMATION* model in Table 3, difficulty arises in comparing results because of differences in data and differences in variables used in the studies. Khanna found that acreage, college attendance, and computer use were statistically significant factors related to the conditional probability of adopting variable-rate fertilizer technology, whereas these factors (*FARMSIZE, COLLEGE,* and *COMPUTER*) were not significant in the conditional *VRFERTLIME* model in Table 4. Three variables not included in our model were statistically significant in Khanna's model—namely, whether the farmer had forward contracts based on product quality, whether the farmer was willing to adopt variable-rate fertilizer technology for a cost subsidy up to 20%, and distance from a fertilizer dealer. In our analysis, a farmer's lack of general knowledge about the costs and potential benefits of precision farming (*PRICEDIFF*) was statistically related to the conditional probability of adopting variable-rate fertilizer technology, but this variable was not included in Khanna's analysis. A variable representing farmer age or experience was statistically significant in both analyses. Although variables representing land tenure and soil quality were statistically significant in both analyses, they had opposite signs. Khanna found that owner-operators were less likely to adopt variable-rate fertilizer technology given adoption of soil testing technology, whereas we found that farmers who owned more of the land they farmed were more likely to adopt variable-rate fertilizer technology given that they had gathered site-specific information. Differences in signs may have resulted from differences in variable construction. For example, Khanna's soil quality variable was the ratio of historical farm yield to average county yield, whereas ours was farm-average lint yield in 2000. Also, Khanna's land tenure variable was a dummy variable indicating whether the farm operator owned the farm, whereas ours was a continuous variable for the number of owned minus rented acres.

Several important conclusions can be drawn from considering the overall marginal effects on the probability of adopting variable-rate fertilizer technology (*VRFERTLIME*) in Table 6 in relation to the marginal effects in Tables 3 and 4. Farmer age (*OVER50*) had statistically significant marginal effects in common among the marginal effects in Tables 3, 4, and 6. Clearly, older farmers were less likely to adopt site-specific information technology than younger farmers (Table 3), 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 4). 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 6).

Land quality (*YIELD*) had a statistically significant positive marginal effect in the *INFORMATION* model (Table 3) and a negative marginal effect in the conditional *VRFERTLIME* model (Table 4) but did not have a statistically significant overall marginal effect on the probability of adopting variable-rate fertilizer technology (Table 6). The unexpected negative marginal effect for *YIELD* in the conditional *VRFERTLIME* model in Table 4 and the positive marginal effect for *YIELD* in Table 3 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*), college attendance (*COLLEGE*), 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 3) and their overall marginal effects (Table 6) were statistically significant, but their marginal effects were not statistically significant in the conditional *VRFERTLIME* model (Table 4). 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 a 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 4) and their overall marginal effects (Table 6) were statistically significant, but their marginal effects were not statistically significant in the *INFORMATION* model (Table 3). 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 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 4 and 6 were not statistically significant for college attendance (*COLLEGE*), but *COLLEGE* significantly affected the probability of adopting site-specific information technology (Table 3). 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 VRT Adoption

The probability of adopting other VRT (*VROTHER*) given *INFORMATION* = 1 was only related to the state in which the farm was located (Table 4); farmers in Alabama and Georgia were more likely to adopt other VRT 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 3). The net result was that *COLLEGE* had a statistically significant overall marginal effect on the probability of adopting other VRT (Table 6). 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 3) did not have significant overall marginal effects on the probability of adopting other VRT (Table 6). The statistically nonsignificant marginal effects in the conditional *VROTHER* model (Table 4) diluted the significant effects of these variables in the *INFORMATION* model (Table 3). For example, *FARMSIZE* and *OVER50* had unexpected signs in the conditional *VROTHER* model (Table 4). 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 VRT (Table 6).

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.

Our 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 to 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.

Our 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 help (1) agribusiness firms promote sales of their variable-rate fertilizer technology products and (2) 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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