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A Binary Logit Estimation of Factors Affecting Adoption of GPS Guidance Systems by Cotton Producers

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Binary logit analysis was used to identify the factors influencing adoption of Global Positioning System (GPS) guidance systems by cotton farmers in 11 Mid-south and Southeastern states. Results indicate that adoption was more likely by those who had already adopted other precision-farming practices and had used computers for farm management. In addition, younger and more affluent farmers were more likely to adopt. Farmers with larger farms and with relatively high yields were also more likely to adopt. Education was not a significant factor in a farmer's decision to adopt GPS guidance systems.

Key Words: binary logit, cotton, GPS guidance system, marginal effect, precision farming, technology adoption

JEL Classifications: Q12, Q16, Q19, Q20, Q24

Precision-agriculture technology is defined as "electronic monitoring and control applied to agriculture, including site-specific application of inputs, timing of operations, and monitoring of crops and employees" (Lowenberg-DeBoer and Boehlje). Precision technologies provide producers with increased information and control of crop growing conditions. Although many of these technologies have been commercially available since the early 1990s, their pace of adoption has been modest (McBride and Daberkow). The adoption of precision-farming technologies depends on the characteristics of the decision maker, farm characteristics, crop markets, and the price/cost of the new technologies (Daberkow, Fernandez-Cornejo, and Padgitt).

The use of precision technology for cotton still lags use in grain crops because accurate yield monitors have only recently become commercially available, though growth in

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variable-rate applications is occurring rapidly (Lowenberg-DeBoer 1999; Martin et al.). The recent addition of Global Positioning System (GPS) units to yield monitoring systems has allowed producers to gain additional information about their fields.[1] Because of its increased precision and accuracy over a foam marker with an experienced applicator (Batte and Ehsani; Buick and White; Ehsani, Sullivan, and Zimmerman; Ehsani et al.; Medlin and Lowenberg-DeBoer), the use of GPS navigation by custom pesticide applicators has grown quickly since 1997 (Medlin and Lowenberg-DeBoer). Crop producers have also begun adopting GPS navigation systems, because of improvements in accuracy, speed, and uniformity of application (Grisso and Alley). A recent survey (Roberts et al. 2006) of cotton producers in 11 Mid-south and Southeastern states suggests that the use of yield monitors with GPS units has more than doubled since 2000. The inclusion of GPS units for yield monitoring or other purposes has allowed the inclusion of one of the newest "add-ons" to these emerging precision-farming technologies, GPS-based guidance systems. Some of these guidance systems use lightbars and GPS to help equipment drivers stay on track. Other more advanced technologies, such as autosteer, actually use GPS to steer the equipment down the row or across the field.

Apart from cost savings, there are certain intangible benefits to GPS guidance technologies. They include reduced operator fatigue; the ability to better visually monitor planters, sprayers, or other equipment and obtain more accurate crop rows; reduced depreciation and maintenance on machinery; more accurate placement of chemical inputs; and the freedom to perform more precise tasks at night or during foggy conditions (Ehsani et al.; Russell; Stalcup). Savings of time, materials, and fuel have also been documented (Batte and Ehsani). However, because they have only recently become commercially available, lack of information and education about the use and economic feasibility of investing in this emerging technology may limit adoption. According to the U.S. Department of Agriculture, in 2003, GPS guidance systems were used on only 5.9% of planted acres in the United States (USDA-ERS).

More important, a study on GPS auto guidance with corn and soybean in the Midwest revealed that the new technology could help farmers boost productivity and expand their farm operations. Further, it showed that farmers would have greater flexibility in choosing employees because it required less skill "since the guidance system [was] doing a lot of the steering and other detailed work" (Lowenberg-DeBoer 2004).

The overall objective of this study was to determine the factors responsible for adoption of GPS guidance systems by cotton producers. Specifically, we were interested in identifying the factors that influence the adoption of GPS guidance systems in precision farming by cotton farmers in the major cotton-producing region consisting of 11 states: Alabama, Arkansas, Florida, Georgia, Louisiana, Mississippi, Missouri, North Carolina, South Carolina, Tennessee, and Virginia. Such information can shed light on differences in determinants of adoption among crops that can serve the specific needs of cotton farmers and ensure the design of successful marketing and extension programs.

Technology adoption literature in general has studied different aspects of adoption, including the costs of adoption (Kurkalova, Kling, and Zhao), impact of adoption on efficiency (Langemeier), different stages of adoption (Barham, Jackson-Smith, and Moon), reversible technology adoption (Baerenklau and Knapp), role of human capital (Foster and Rosenzweig; Rahm and Huffman), risk (Marra and Carlson), and simultaneous adoption of technology and productivity (McBride and El-Osta; Zepeda 1994). A review of literature in precision farming with regard to its profitability and future and crop- and technology-specific benefits from precision farming appear in Griffin et al. The adoption of site-specific information and variable-rate

[1] According to a recent study by Larson and Roberts, farmers who adopted yield monitors with GPS perceived significantly higher field spatial yield variability in cotton, peanut, and wheat. In general, farmers who used other site-specific information technologies did not perceive spatial yield variability that was different from nonadopters.

technologies has been studied in the past (e.g., El-Osta and Mishra; Isik and Khanna; Khanna; Roberts et al. 2004, 2006), including sequential adoption (e.g., Khanna), as well as the adoption of autoguidance systems in the production of other crops (e.g., Lowenberg-DeBoer 2004). The adoption of GPS guidance systems in cotton production is on the forefront of technology adoption, and, given that cotton is a relatively high-valued crop with relatively high input use, studies on adoption rates are paramount to increasing the use of more efficient production practices. In addition, given the yield and production efficiency possibilities with GPS guidance systems in cotton production, this is an important area of emerging empirical research that will facilitate discussion and future research within the agricultural economics profession.

Empirical Model

A random utility model was used to determine the probability that a cotton producer would choose to adopt a GPS guidance system. Following Ben-Akiva and Lerman and Louviere, Hensher, and Swait, a random utility model is defined as

$$U_{in} = V_{in} + \varepsilon_{in}, \quad i = 1, \ldots, I \text{ and } n = 1, \ldots, N, \tag{1}$$

where U_{in} is the nth farmer's expected utility accruing from choosing alternative i, V_{in} being the deterministic portion of utility (to be maximized), and ε_{in} is the stochastic component. The probability that n chooses i is

$$\begin{aligned} P_n(i) &= \Pr\left(U_{in} \geq U_{jn}\right) \\ &= \Pr\left(V_{in} + \varepsilon_{in} \geq V_{jn} + \varepsilon_{jn}\right) \\ &= \Pr\left(\varepsilon_{jn} - \varepsilon_{in} \leq V_{in} - V_{jn}\right), \\ &\text{for all } i, j \in C_n, \end{aligned} \tag{2}$$

where C_n is the choice set for producer n [$C_n = \{i, j\} = \{\text{Adopt, Don't Adopt}\}$].[2]

Assuming the random errors in Equation (1) are independently and identically distributed across the I alternatives ($i = 1, \ldots, I$) and N individuals ($n = 1, \ldots, N$) as a type I extreme value distribution, that is, $\varepsilon_n = \varepsilon_{jn} - \varepsilon_{in}$ in Equation (2) is logistically distributed, Ben-Akiva and Lerman have shown that the probability of producer n choosing alternative i is given by

$$P_n(i) = \frac{e^{\mu V_{in}}}{\sum\limits_{j \in C_n} e^{\mu V_{jn}}}, \tag{3}$$

where $\mu > 0$ is the scale parameter, assumed equal to one, because it is unidentifiable within any particular data set (Lusk, Roosen, and Fox) and cannot be distinguished from the overall scale of the estimated coefficients of the linear parameters, βs (Ben-Akiva and Lerman). With two choices ($i = 1$ and $j = 0$), a binary logit model gives the choice probability for alternative i as (Ben-Akiva and Lerman; Judge et al.)

$$\begin{aligned} P_n(i = 1) &= \frac{e^{\mu V_{in}}}{e^{\mu V_{in}} + e^{\mu V_{jn}}} \\ &= \frac{1}{1 + e^{-\mu\left(V_{in} - V_{jn}\right)}} \\ &= \Phi(\boldsymbol{V}) \\ &= \Phi(\boldsymbol{\beta}'\boldsymbol{x}), \end{aligned} \tag{4}$$

where $\boldsymbol{\beta}'$ is the vector of parameters to be estimated and $\boldsymbol{x}$ is the vector of observations.[3]

Assuming that V_{in} and V_{jn} are linear in their parameters, the indirect utility function of alternative i ($i = 1$) for respondent (producer) n to be estimated is given by

$$\begin{aligned} GPS_{in} = \beta_0 &+ \beta_1 SIZE_n + \beta_2 YIELD_n \\ &+ \beta_3 AGE_n + \beta_4 EDUC_n \\ &+ \beta_5 OPFP_n + \beta_6 COMP_n \\ &+ \sum_{y=7}^{11} \beta_y INCOME_n + \\ &+ \sum_{s=12}^{21} \beta_s STATE_n + \varepsilon'_n, \end{aligned} \tag{5}$$

[2] The terms "producer," "farmer," and "respondent" are used interchangeably in this paper. In applying random utility theory, the farmer is assumed to be a consumer faced with a choice between adopting and not adopting the new technology (GPS guidance systems), which is an input in his or her portfolio.

[3] Consistent parameter estimates are obtained by maximizing the associated log-likelihood function ln $L = \sum_{n=1}^{N} \{Y_{in} \ln[\Phi(V)] + Y_{jn} \ln[\Phi(V)]\}$, where Y_{in} and Y_{jn} represent the dependent variables under choices i and j, respectively (Florkowski and Bilgic).

where GPS_{in} is a notational replacement for V_{in}, identifying those respondent farmers who adopted GPS-based guidance systems for cotton production; β_0 through β_{21} are the parameters to be estimated, β_0 being the alternative-specific constant; and ε'_n is the random error term.[4] The explanatory variables are fully defined in Table 1. They include the farm characteristics of size (*SIZE*) and lint yield (*YIELD*),[5] the latter being used as a proxy for land quality, and the farmer characteristics of age of the respondent farmer (*AGE*), his or her education level (*EDUC*), whether or not he or she used other precision-farming practices (*OPFP*) or computers for farm management (*COMP*), and five dummies for gross household income level (*INCOME*). In addition, 10 dummy variables were included to account for location differences among the 11 states (*STATE*).[6]

Marginal effects (Greene; Maddala) were used to measure changes in probability of adopting one or more GPS guidance system(s) due to given changes in the explanatory variables (Liao; Long). Marginal effects of continuous variables were calculated at the means of the data.[7] For dummy variables, a value of 0 was used if the mean was less than 0.5 and a value of 1 if the mean was greater than or equal to 0.5 (Obubuafo et al.; D. Schlotzhauer, pers. comm.).[8]

Data

A mail survey was conducted in late winter 2005. Following Dillman's general mail survey procedures, a copy of the questionnaire and a cover letter were sent to a total of 12,245 potential cotton producers in the 11 states on January 28, 2005. A postcard reminder was sent on February 4, 2005, followed by a second mailing on February 23, 2005. The mailing list of potential cotton producers for the 2003–2004 planting season was provided by the Cotton Board in Memphis, Tennessee (B.

[4] On careful inspection of the model, one or more of the explanatory variables *SIZE*, *YIELD*, *OPFP*, and *INCOME2–INCOME6* may appear to be "potentially endogenous" with the dependent variable, *GPS*. Therefore, the issue of endogeneity was studied by actually modeling simultaneous equations and using maximum likelihood estimation. If there were specification errors in the original structural model, the systems methods would transmit such errors and the finite-sample variation in the estimated covariance matrix through the system (Greene). Supposedly, the greater the number of equations in the simultaneous-equations system, the more likely would this transmission occur in the entire system. Thus, assuming that the "potentially endogenous" explanatory variables were each in fact endogenous and hence simultaneously determined with the dependent variable, *GPS*, each was modeled simultaneously in a two-equation simultaneous system with GPS guidance technology adoption. None of the resulting estimated coefficients of interest was significant even at the 10% level. In addition, the error correlation between equations in none of the systems was significant. This was repeated for *INCOME* as one composite variable in a system with *GPS* as well as a system with *INCOME2–INCOME6* and *GPS* (six equations), still resulting in no statistical significance in the variables of interest or error correlation across the equations.

Assuming asymptotic normality of the error terms, endogeneity was also tested for each of these "potentially endogenous" explanatory variables using classical Hausman specification tests, and the null hypothesis of no endogeneity could not be rejected between any of the chosen variables and GPS guidance technology adoption (Rivers and Vuong; Wooldridge). Hence, the likelihood of a type II error in respect of endogeneity could be dismissed.

[5] Nonrepresentative yields (below 200 lbs./acre and above 2,200 lbs./acre) were not used for this analysis.

[6] The model does not incorporate variables like land tenure, type of farm organization, participation in crop insurance, and participation in income and/or price support programs, thus lending itself to potential bias due to omitted variables. For example, the income dummy variables may be correlated with one or more of those omitted variables. The data collected were not sufficient to incorporate those variables in the article. However, in keeping with previous literature related to adoption analysis, appropriate variables were included in the survey and used in the model.

[7] In sufficiently "large samples," marginal effects calculated by averaging the individual marginal effects at each observation (Bell et al.; Neter, Wasserman, and Kutner; Pindyck and Rubinfeld) would give the same results obtained here from the means of the data (Greene) by adding an observation with all means and calculating the marginal effects at that point.

[8] Anderson and Newell have developed a novel way of simplifying the calculation of marginal effects in logit and probit models (making them a function of only the estimated constant term) and their associated asymptotic variances by normalizing the explanatory variables at any desired value.

Skorupa, pers. comm.). This constituted all known cotton producers in those 11 states. A total of 1,215 usable surveys were returned. Another 202 returned surveys were unusable (18 were returned undeliverable, and 184 indicated they were not cotton farmers or had retired). These addresses were deleted from the list of potential cotton producers, leaving 12,043 cotton producers who received the survey and hence a response rate of approximately 10%.

In addition to questions related to the many aspects of precision farming, producers were asked about themselves, their farm, and their farming practices, including if they used lightbar, autosteer, or other forms of GPS guidance systems. A producer was considered an adopter of a GPS guidance system if he or she used either a lightbar, autosteer, or any other GPS guidance system(s). In addition, respondents were asked demographic questions concerning their age, years farming, education, income, and farm size.

Except age and location, all other variables were hypothesized to have positive signs on their estimated coefficients (Table 1). To avoid perfect collinearity, farmers with incomes lower than $50,000 (categorized as *INCOME1*) were excluded from the set of dummies. A positive sign on any of the income dummies (*INCOME2–INCOME6*) would mean that farmers in that particular income category had a higher probability of adopting GPS guidance technology than farmers with incomes less than $50,000 (Bell et al.; Govindasamy, Italia, and Adelaja; Jarvis). Age was expected to have a negative sign, consistent with previous findings that older producers are less likely to adopt (e.g., Roberts et al. 2004). Since it was difficult to speculate on reasons for differences among states, the signs of the location variables could not be hypothesized *a priori* (Roberts et al. 2004). Mississippi returned the highest number of responses and thus was omitted from the model and used as a comparison with each of the other ten states.

Results

The likelihood ratio test suggested the estimated model had a good fit with a statistically significant score of 197.20 at the 1% level, indicating a strong relationship between the probability of a responding cotton producer's adoption of one or more GPS guidance system(s) and the explanatory variables. The McFadden R^2 was approximately 0.20, which falls in the lower limit of the range 0.20 to 0.40 that is considered an "extremely good fit" (Hensher and Johnson), suggesting a relationship between adoption of GPS guidance technology and the regressors included in the model (Amemiya; Ben-Akiva and Lerman; Judge et al.). Prediction success statistics indicated that the model correctly predicted about 80% of the responses (Table 2).

Maximum likelihood estimates of all parameters used in the model revealed their expected signs (Table 1). The coefficients of all variables, except *EDUC* and the dummy variables for Alabama (*AL*), Arkansas (*AR*), Louisiana (*LA*), South Carolina (*SC*), and Tennessee (*TN*), were significantly different from zero at least at the 5% level. Therefore, farmers in the states of Florida (*FL*), Georgia (*GA*), Missouri (*MO*), and Virginia (*VA*) were more likely to adopt GPS guidance systems in cotton farming than farmers in Mississippi (*MS*).[9]

Farm size, yield, and age were also significant in the Roberts et al. (2004) study on adoption of site-specific information technology (SIT) and variable-rate technologies (VRT) for cotton precision farming in six Southeastern states, though farm size and experience were not significant in Khanna's study on precision-farming technology adoption in four Midwestern states. However, while farm size was significant in McBride and Daberkow's multivariate logit regression model on precision farming adoption in the United States, farmer age was not. Like in Khanna's model as well as Roberts et al.'s (2004) model on VRT adoption, education/college attendance was not a significant factor in the adoption of GPS guidance systems. However, this contradicts McBride and Da-

[9] It may be noted, however, that the states of Florida, Missouri, and Virginia each had a relatively small number of observations used in the regression: 17, 33, and 23, respectively (Table 1).

Table 1. Summary of Variables Used in the Binary Logit Model[a]

		Mean (Standard Deviation)		
Variable[b]	Definition (Frequency Used in Regression)	Population	Adopter	Nonadopter
Dependent variable				
GPS	Used one or more GPS guidance system(s) (yes = 1 = 227, no = 0 = 652)	0.26[c]	1.00	0.00
Explanatory variables				
Farm characteristics				
SIZE	Cotton acres (dryland and irrigated) planted in farm on average in 2004	792.05 (950.58)	1,288.70 (1,397.04)	619.13 (652.04)
YIELD[d]	Average cotton yield (dryland and irrigated) in pounds per acre in 2004	910.60 (234.04)	986.89 (193.27)	884.04 (241.19)
Farmer characteristics				
AGE	Age in years during survey	50.00 (11.56)	46.13 (11.31)	51.34 (11.36)
EDUC	Years of formal education, excluding kindergarten	14.26 (2.26)	14.63 (2.03)	14.13 (2.32)
OPFP	Other precision-farming practices (yes = 1 = 448, no = 0 = 431)	0.51[c]	0.71	0.44
COMP	If used a computer for farm management (yes = 1 = 496, no = 0 = 383)	0.56[c]	0.75	0.50
INCOME2[e]	Estimated pretax household income of respondent in 2004 from both farm and nonfarm sources: \$50,000 to \$99,999 (yes = 1 = 290, no = 0 = 589)	0.33[c]	0.34	0.33
INCOME3[e]	Estimated pretax household income of respondent in 2004 from both farm and nonfarm sources: \$100,000 to \$149,999 (yes = 1 = 180, no = 0 = 699)	0.20[c]	0.21	0.20
INCOME4[e]	Estimated pretax household income of respondent in 2004 from both farm and nonfarm sources: \$150,000 to \$199,999 (yes = 1 = 76, no = 0 = 803)	0.09[c]	0.07	0.09
INCOME5[e]	Estimated pretax household income of respondent in 2004 from both farm and nonfarm sources: \$200,000 to \$499,999 (yes = 1 = 129, no = 0 = 750)	0.15[c]	0.15	0.15
INCOME6[e]	Estimated pretax household income of respondent in 2004 from both farm and nonfarm sources: \$500,000 or above (yes = 1 = 101, no = 0 = 778)	0.11[c]	0.19	0.09
Farm location (*STATE*)[f]				
AL	Farm in Alabama (yes = 1 = 114, no = 0 = 765)	0.13[c]	0.11	0.14
AR	Farm in Arkansas (yes = 1 = 64, no = 0 = 815)	0.07[c]	0.09	0.07
FL	Farm in Florida (yes = 1 = 17, no = 0 = 862)	0.02[c]	0.02	0.02
GA	Farm in Georgia (yes = 1 = 155, no = 0 = 724)	0.18[c]	0.15	0.19
LA	Farm in Louisiana (yes = 1 = 64, no = 0 = 815)	0.07[c]	0.06	0.08
MO	Farm in Missouri (yes = 1 = 33, no = 0 = 846)	0.04[c]	0.06	0.03
NC	Farm in North Carolina (yes = 1 = 150, no = 0 = 729)	0.17[c]	0.17	0.17
SC	Farm in South Carolina (yes = 1 = 53, no = 0 = 826)	0.06[c]	0.04	0.07
TN	Farm in Tennessee (yes = 1 = 81, no = 0 = 798)	0.09[c]	0.10	0.09
VA	Farm in Virginia (yes = 1 = 23, no = 0 = 856)	0.03[c]	0.05	0.02

Table 1. (Continued)

[a] Total number of observations, $N = 879$.

[b] Except age and location, all other variables were hypothesized to have positive signs on their estimated coefficients. Age was expected to have a negative sign, and the signs of the location variables could not be hypothesized *a priori* since it was difficult to speculate on reasons for differences among states.

[c] The mean of each dummy variable represents the share of observations with the relevant characteristic. For example, 26% of farmers surveyed used GPS guidance systems, 51% practiced other types of precision farming, and 56% used computers for farm management.

[d] Nonrepresentative yields (below 200 lbs./acre and above 2,200 lbs./acre) were considered outliers and deleted. Dryland and irrigated cotton lint yields were averaged.

[e] *INCOME1* (below $50,000), with frequency 103 (population mean = 0.12, adopter mean = 0.04, nonadopter mean = 0.15), was captured in the constant and thus omitted to facilitate its comparison with other income levels. A positive sign on any of the income dummies would mean that farmers in that particular income category had a higher probability of adopting GPS guidance systems than farmers with incomes less than $50,000.

[f] The dummy variable for the state of Mississippi (*MS*), with 125 observations (population mean = 0.14, adopter mean = 0.16, nonadopter mean = 0.14), was omitted. This facilitates comparison of adoption probabilities in Mississippi with the other 10 states.

berkow and even Roberts et al.'s (2004) finding on college education for the latter's SIT adoption model. Therefore, results on precision-farming adoption in general are not consistent across studies for farm size, crop yield, farmer age/experience, and education.[10]

In keeping with Daberkow and McBride and McBride and Daberkow, computer knowledge was a significant factor for adoption of GPS guidance systems, though it was not related to adoption in Roberts et al. (2004). Computer adopters for farm management and adopters of other precision-farming practices tended to be adopters of GPS guidance system technology, which is in keeping with the findings of Zepeda (1990) as well as Kim, Westra, and Gillespie. The positive influence of the income categorical variables on adoption is consistent with the findings of Bell et al.

Marginal effects suggest farmers who used other precision-farming technologies (*OPFP*) or computers for farm management (*COMP*) were 3.0% and 3.2% more likely to adopt a GPS guidance system, respectively, than those who did not use other technologies or computers (Table 2). This is obviously because the marginal cost of adding a GPS guidance system becomes considerably lower when one already owns another precision-farming technology or a computer (Smith et al.).[11] Similarly, a 1-year increase in age (*AGE*) resulted in a 0.2% decrease in the probability of adoption of a GPS guidance system. The marginal effects of farm size (*SIZE*) and lint yield (*YIELD*) suggest that an acre or a pound increase in farm size or lint yield increased the probability of adoption of a GPS guidance system by 0.01% or less.

[10] In this connection, it is worth noting that adoption of technology is known to be a dynamic process. For example, Rogers observes adoption to be more responsive to farm size at the "innovator" stage, its effect gradually diminishing as diffusion increases. The dependence of herbicide-tolerant corn on farm size in Fernandez-Cornejo, Daberkow, and McBride's study confirms this.

[11] In Smith et al.'s study of the Great Plains, college education, outside employment, friends, and family influenced adoption of computer and Internet use more than farmer age or farm size.

Table 2. Parameter Estimates and Marginal Effects from the Binary Logit Model

Explanatory Variable	Estimate (Standard Error)	Wald χ^2	Marginal Effect[a] (Standard Error)
Constant***	−4.5169 (1.0250)	19.4194	−0.2272 (0.0516)
*SIZE****	0.0007 (0.0001)	30.4811	<0.0001 (<0.0001)
*YIELD****	0.0017 (0.0005)	12.6552	0.0001 (<0.0001)
*AGE****	−0.0351 (0.0084)	17.3125	−0.0018 (0.0004)
EDUC	0.0323 (0.0434)	0.5551	0.0016 (0.0022)
*OPFP****	0.5880 (0.1918)	9.3938	0.0296 (0.0096)
*COMP****	0.6310 (0.1999)	9.9600	0.0317 (0.0101)
*INCOME2****	1.4537 (0.4476)	10.5491	0.0731 (0.0225)
*INCOME3****	1.3356 (0.4638)	8.2937	0.0672 (0.0233)
*INCOME4***	1.2021 (0.5278)	5.1861	0.0605 (0.0265)
*INCOME5****	1.3847 (0.4828)	8.2265	0.0696 (0.0243)
*INCOME6****	1.7065 (0.4858)	12.3418	0.0858 (0.0244)
AL	0.3774 (0.3719)	1.0299	0.0190 (0.0187)
AR	0.2341 (0.3918)	0.3570	0.0118 (0.0197)
*FL***	1.3780 (0.6836)	4.0628	0.0693 (0.0344)
*GA***	0.7613 (0.3659)	4.3301	0.0383 (0.0184)
LA	−0.1018 (0.4124)	0.0610	−0.0051 (0.0207)
*MO***	1.0005 (0.4835)	4.2820	0.0503 (0.0243)
*NC**	0.5553 (0.3279)	2.8677	0.0279 (0.0165)
SC	0.0209 (0.4648)	0.0020	0.0011 (0.0234)
TN	0.2600 (0.3704)	0.4926	0.0131 (0.0186)
*VA****	1.8272 (0.5165)	12.5170	0.0919 (0.0260)

Notes: Likelihood ratio test: $\chi^2 = 197.195$ (d.f. = 21); critical $\chi^2 = 38.93$; Prob > χ^2: <0.0001. McFadden $R^2 = 0.196$; adjusted McFadden $R^2 = 0.175$. Prediction success: concordant 79.7%, discordant 20.1%, tied 0.2%. Number of observations = 879; number of GPS guidance system adopters (*GPS* = 1) = 227; number of GPS guidance system nonadopters (*GPS* = 0) = 652. State dummy variables compare adoption relative to cotton farmers in Mississippi (*MS*); *INCOME* variables compare adoption relative to cotton farmers with incomes below $50,000 (*INCOME1*); ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

[a] A marginal effect indicates the change in predicted probability of adopting one or more GPS guidance system(s) for a unit change in an explanatory variable. Marginal effects of continuous variables were calculated at the means of the data. For dummy variables, a value of 0 was used if the mean was less than 0.5 and a value of 1 if the mean was greater than or equal to 0.5.

Marginal effects for the income dummy variables (*INCOME2–INCOME6*) indicate that respondents in these income categories were, respectively, 7.3%, 6.7%, 6.1%, 7.0%, and 8.6% more likely to adopt a GPS guidance system than respondents with incomes below $50,000 (*INCOME1*). Marginal effects for the state dummy variables indicate that respondents from Florida, Georgia, Missouri, and Virginia were more likely to adopt a GPS guidance system by 7.0%, 3.8%, 5.0%, and 9.2%, respectively, than respondents from Mississippi.

Conclusions

High-value, high-input crops, such as cotton, have the potential for profitable adoption of precision farming. Identifying the characteristics that influence cotton farmers to adopt GPS guidance systems as one of its newest "add-ons" in cotton production may help extension personnel target their education and training programs toward farmers who are more likely to adopt these technologies and to benefit from their programs. Further, agribusiness firms may benefit from the results of this research to develop features and benefits that are important to cotton producers.

With the assumption that farmers maximize expected utility, a binary choice model was specified to represent the dichotomous decision to adopt GPS guidance technology, and a logit procedure was used to fit the model. The probability of adoption of GPS guidance systems was assumed to depend on factors such as farm size, cotton lint yield, age, education level, adoption of other precision-farming practices and computer use, income, and location. The estimated model was then used to evaluate the response of an individual having mean characteristics. Marginal effects were calculated to measure the effects of changes in the explanatory variables on the probability of adoption.

Overall, the results indicate that information and/or knowledge gleaned from the use of other precision-farming technologies and computer use for farm management are more influential in a producer's decision to adopt GPS guidance systems than general education. Therefore, a target of education and training by extension personnel and a focus of marketing efforts by agribusiness firms on farmers who are using other precision-farming technologies and computers for farm management will increase the probability of success in reaching cotton farmers interested in extension education programs and purchases of GPS guidance technology. Extension education and training, and agribusiness marketing efforts directed toward farmers who have received college education are not as likely to increase GPS guidance technology adoption. In addition, younger, more affluent farmers are more likely to adopt, as found in past studies of technology adoption. Cotton farmers with larger farms or with relatively high lint yields are also more likely to adopt. Future research could involve similar analysis with time-series or cross-sectional time-series data and a specific analysis related to simultaneous estimation of given variables/models examining, for example, the adoption process as well as the impact of adoption on yields and/or farm income.

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