FACTORS INFLUENCING THE TIMING OF PRECISION AGRICULTURE TECHNOLOGY ADOPTION IN SOUTHERN U.S. COTTON PRODUCTION

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ABSTRACT

The timing of technology adoption is influenced by farmer ability to bear risk; innovators are more risk tolerant than laggards. The factors influencing early adoption of precision agriculture (PA) technologies by cotton farmers are important for anticipating technology diffusion over time. Tobit models were used to evaluate the factors influencing the timing of yield monitoring (YMR), remote sensing (RMS) and grid soil sampling (GSS) adoption in cotton production. Results for YMR show that younger farmers with higher yields and incomes, who used other PA technologies (e.g., computers and handheld PDAs), and thought PA would improve environmental quality and would be profitable and important in the future adopted YMR earlier than other farmers. Farmers who relied on farm dealers, consultants and the Internet for PA information adopted YMR later than others. Younger farmers with farms in Arkansas and Missouri, who used other PA technologies, thought PA would be profitable in the future and relied on tradeshows and news media for PA information adopted RMS earlier than others. Those who relied on PA information from consultants adopted RMS later than others. Younger farmers who owned more of the land they farmed, used computers and other PA technologies, thought PA would improve environmental quality, and relied on PA information from consultants adopted GSS earlier than others. Farmers in Georgia, Virginia and Texas, who used YMR and handheld PDAs and relied on the Internet for PA information adopted GSS later than others.

Keywords: Economics, grid soil sampling, precision agriculture, remote sensing, technology adoption, yield monitoring

INTRODUCTION

Precision agriculture (PA) became available in the late 1980s (Griffin et al., 2004). Since then many researchers have investigated the factors influencing the decision to adopt PA technologies. For example, yield monitoring (e.g., Marra et al., 2010), remote sensing (e.g., Larson et al., 2008) and soil sampling (e.g, Khanna, 2001) have been evaluated for adoption decisions made at or before a specific point in time. However, little research has been conducted to determine the factors influencing the timing of adoption after a specific PA technology becomes available. The passage of time influences the adoption of a new technology as producers first become aware of the technology, decide to adopt it, implement it, and confirm that their adoption decision was correct (Rogers, 1995). With one exception (Roberts et al., 2004b), no literature has identified the factors influencing the timing of the adoption decision. This research identifies the factors influencing cotton farmer decisions to adopt yield monitoring (YMR), passive remote sensing—defined here as satellite imagery and/or aerial photography—(RMS), and grid soil sampling (GSS) at different points in time after these technologies became commercially available.

The results of this study provide information that could help farmers make technology adoption decisions now and in the future (Diekmann and Batte, 2010). Additionally, results from this study can be used by researchers to put PA technology adoption and diffusion into a historical perspective for future research (e.g., Griffin et al., 2010). Also, machinery manufacturers and agricultural retailers might use the results to anticipate future demand for PA technologies (Fountas et al., 2005).

CONCEPTUAL FRAMEWORK

Assume cotton producer i confronts a discrete choice to adopt PA technology j at time t_0, the year when the technology first becomes commercially available.

Let $E\left[U_{AD}\left(\pi_{ijt}^{AD}\right)\right]$ be the expected utility from adoption in year $t \geq t_0$ and $E\left[U_{NA}\left(\pi_{ijt}^{NA}\right)\right]$ be the expected utility from not adopting in year *t*. Additionally, let π_{ijt}^{AD} be profit with adoption in *t* and π_{ijt}^{NA} be profit without adoption in *t*. Defining $U_{ijt}^{*} = E\left[U_{AD}\left(\pi_{ijt}^{AD}\right)\right] - E\left[U_{NA}\left(\pi_{ijt}^{NA}\right)\right]$, so the producer will adopt in year *t* if $U_{ijt}^{*} > 0$ and will not adopt if $U_{ijt}^{*} < 0$ (Khanna, 2001). The farmer cannot adopt in years $t < t_0$ before the technology becomes available.

Ben-Akiva and Lerman (1985) identified a random utility model:

$$U_{ijt}^{*} = \beta' x_{ijt} + \varepsilon_{ijt}, \tag{1}$$

where U_{ijt}^{*} is the difference in utility from adopting and not adopting PA technology j by farmer i in year *t* and x_{ijt} represents the exogenous variables (x_{ij}) that are hypothesized to influence adoption in year *t*.

DATA

Data for this study were obtained from the Cotton Incorporated Southern PA Survey conducted in February and March of 2009 for the 2008 crop. The survey was conducted to determine the current use of PA technologies in 12 states (Mooney et al., 2010). Farmers were asked in the survey to report the number of years they had used each specific PA technology. Of the 913 useable responses, 55, 45 and 133 farmers reported using YMR, RMS and GSS for one or more years, respectively. We used the number of years a farmer reported using these technologies to approximate the year (t_{ij}) the farmer adopted the technology:

$$t_{ij} = 2009 - YR_{ij}, \tag{2}$$

where YR_{ij} is the number of years farmer i reported using technology j in 2009 when the survey was conducted. Thus, a larger YR_{ij} indicates farmer *i* adopted the technology sooner after it became commercially available than other farmers.

The survey data were aligned with the Agricultural Census (USDA, 2007) population of cotton farmers using post-stratification weights to adjust for differences between the sample and the population (Gelman and Carlin, 2001). A matrix was used to classify the weights as the numbers of cotton farms in six farm-size categories (0.40–40.06, 40.47–100.77, 101.17–201.94, 202.34–404.28, 404.68–808.97, ≥809.37 cotton ha) and the numbers of cotton farms in each of the 12 southern states (Harper, 2011; USDA, 2007).

Farmers who reported using YMR more than 13 years were excluded from the sample because cotton yield monitors became commercially available in 1997 (Perry et al., 2001). Also, farmers who reported using RMS and GSS more than 18 years were excluded because GPS-related RMS and GSS were not available before 1992 (Enstrom, 2007).

METHODS AND PROCEDURES

The number of years using a technology is censored at zero, with a zero observation indicating non-adoption and a positive observation indicating use of the technology for one or more years. Assuming normality and continuous time, Tobit regression methods (Tobin, 1958) were used to determine the factors associated with the timing of adoption. Three Tobit models were specified for farmer *i* and technology *j* (*j* = YMR, RMS and GSS) as follows (Greene, 2012):

$$YR_{ij}^{*} = \beta' x_{ij} + \varepsilon_{ij}\ , \quad \varepsilon_{ij} \sim N(0, \sigma^2), \tag{3}$$

where β is a vector of unknown parameters, x_{ij} represents factors that affect YR_{ij}^{*}, ε_{ij} is an error vector, and the distribution of YR_{ij}^{*}, given x_{ij}, is $YR_{ij}^{*}|x_{ij} \sim N(\beta x_{ij}, \sigma^2)$.

The observed value of $YEARS_{ij}$ is (Greene, 2012):

$$YR_{ij} = \begin{cases} YR_{ij}^{*} & if\ YR_{ij}^{*} > 0 \\ 0 & if\ YR_{ij}^{*} \leq 0\,. \end{cases} \tag{4}$$

If $YR_{ij} > 0$ (uncensored observation), farmer *i* adopted PA technology *j* in year t_{ij}, but if $YR_{ij} = 0$ (censored observation), farmer *i* did not adopt PA technology *j*.

The marginal effect with censoring at zero on the expected value of $YEARS_{ij}^{*}$ for technology *j* is (Greene, 2012):

$$\partial E[YR_{ij}^{*}|x_{ij}, YR_{ij} > 0]/\partial x_{ijk} = \beta_k \Phi(\frac{\beta' x_{ij}}{\sigma}), \tag{5}$$

where Φ is the standard normal distribution function.

The marginal effect for a dummy variable is the difference between the expected values of YR_{ij}^{*} when the dummy variable changes from 0 to 1, holding other variables constant (Greene, 2012):

$$E\left[YR_{ij}^{*}|x_{ij}, x_{ijk} = 1\right] - E\left[YR_{ij}^{*}|x_{ij}, x_{ijk} = 0\right]. \tag{6}$$

The following model was specified to determine the factors influencing the point in time farmer i adopted PA technology j (j = YMR, RMS or GSS):

$$\begin{aligned} YR_{ij} = {} & \beta_0 + \beta_1 FARMSIZE_{ij} + \beta_2 YIELD_{ij} + \beta_3 TENURE_{ij} + \beta_4 LIVESTOCK_{ij} \\ & + \beta_5 (AGE_j)_{ij} + \beta_6 EDUCATION_{ij} + \beta_7 COMPUTER_{ij} + \beta_8 LAPTOP_{ij} \\ & + \beta_9 MEDINCOME_{ij} + \beta_{10} HIGHINCOME_{ij} + \beta_{(11\text{-}13)} (YR_k \geq YR_j)_{ij} \\ & + \beta_{14} PROFITABLE_{ij} + \beta_{15} IMPORTANCE_{ij} + \beta_{16} COTQUALITY_{ij} \\ & + \beta_{17} ENVIQUALITY_{ij} + \beta_{18} FARMDEALER_{ij} + \beta_{19} CONSULTANT_{ij} \\ & + \beta_{20} UEXTENSION_{ij} + \beta_{21} FARMERS_{ij} + \beta_{22} TRADESHOW_{ij} \end{aligned} \tag{7}$$

$$+\beta_{23}INTERNET_{ij} + \beta_{24}NEWSMEDIA_{ij} + \beta_{25}ALFL_{ij} + \beta_{26}AR_{ij} + \beta_{27}GA_{ij}$$
$$+\beta_{28}LA_{ij} + \beta_{29}MO_{ij} + \beta_{30}MS_{ij} + \beta_{31}NC_{ij} + \beta_{32}SC_{ij} + \beta_{33}TN_{ij} + \beta_{34}VA_{ij} + \varepsilon_{ij},$$

where the variables are defined in Table 1, $\beta_0 \ldots \beta_{34}$ are parameters estimated by Tobit regression, and ε is a random error term.

Table 1 includes the hypothesized signs of the explanatory variables in equation (7). A positive hypothesized sign indicates that an increase in the explanatory variable is expected to encourage the farmer to use the technology for more years, suggesting earlier adoption after the technology became commercially available (see equation 2). A negative hypothesized sign has the opposite expectation. The rationales for the expected signs are presented below.

Four farm characteristics were hypothesized to influence the timing of adoption. Many researchers hypothesized farm size (*FARMSIZE*) to positively affect adoption (Roberts et al., 2004a; Walton et al., 2010a). Farmers with larger farms may be less risk averse than farmers with smaller farms because of their ability to bear risk and, therefore, they may be more willing to adopt new technologies earlier than farmers with smaller farms. Roberts et al. (2004a, 2004b) and Walton et al. (2010b) hypothesized that land quality (*YIELD*) positively influences the adoption of PA technologies. Better land quality may motivate farmers to investigate spatial variability and increase the level of management within their fields, increasing the likelihood of earlier adoption of new technologies. Land tenure (*TENURE*) was hypothesized to influence early PA technology adoption (Khanna, 2001; Walton et al., 2010a). Farmers who own more of the land they farm may adopt earlier to preserve the productivity of their own crop fields (Roberts et al., 2004a). Many researchers hypothesized livestock production (*LIVESTOCK*) to have a negative effect on PA adoption (Fernandez-Cornejo et al., 1994). Management of an enterprise not relate to cropland could reduce the time needed to manage field crops (Fernandez-Cornejo et al., 1994), encouraging the farmer to delay adoption of new PA technologies.

Six farmer characteristics were expected to be positively correlated with early adoption. Many researchers hypothesized that age (*AGE*) negatively affects PA adoption (Isgin et al., 2008; Roberts et al., 2004a, 2004b). Younger farmers have longer time horizons and, therefore, have more incentive to change than older farmers. They also have more exposure to and familiarity with new technologies in general, making them more likely to adopt new PA technologies earlier than older farmers. Batte et al. (1990) and Roberts et al. (2004b) hypothesized education (*EDUCATION*) to have a positive effect on PA adoption. More educated farmers may be able to better understand the use of complex technologies, increasing their likelihood of early adoption compared to farmers with less education. Many studies hypothesized the use of a computer for farm management (*COMPUTER*) or a laptop/handheld PDA in the field (*LAPTOP*) to positively influence PA adoption (Roberts et al., 2004a, 2004b; Walton et al., 2010a). Because a computer is a technology used to collect, convey and manipulate data within a field (Walton et al., 2010a), use of a computer may affect the timing of adoption. Additionally, the use of laptop/handheld PDA in a field may enhance the efficiency with which farmers can collect and store field data, increasing their desire to adopt earlier (Walton et al., 2010a).

Table 1. Definitions and Hypothesized Signs for Dependent and Explanatory Variables Used in Tobit Regressions.

Variable	Definition	Sign
Dependent Variables		
YR_j	Number of years farmer used technology *j* (*j*=YMR, RMS, GSS)	
Explanatory Variables		
FARMSIZE	Area (405 ha units) of cotton farmed in 2007 or 2008 (year of largest area)	+
YIELD	Lint yield (1,115 kg/ha units) in 2007 or 2008 (year of largest area)	+
TENURE	Ratio of rented to total land farmed in 2007 or 2008 (year of largest cotton area)	–
LIVESTOCK	Farmer owned livestock (yes=1; else=0)	–
AGE_j	Age when farmer adopted PA technology *j* (*j*=YMR, RMS, GSS) (age in 2009 − YR_j)	–
EDUCATION	Farmer had more than 12 years formal education (yes=1; else=0)	+
COMPUTER	Farmer used computer for farm management (yes=1; else=0)	+
LAPTOP	Farmer used laptop or handheld PDA in the field (yes=1; else=0)	+
LOWINCOME[1]	2007 taxable household income less than $100,000 (yes=1; else = 0)	NA
MEDINCOME	2007 taxable household income between $100,000 and $199,999 (yes=1; else = 0)	+
HIGHINCOME	2007 taxable household income $200,000 or greater (yes=1; else=0)	+
$YR_k \geq YR_j$[2]	*k*=YMR, RMS, GSS, OTHERS; j=YMR, RMS, GSS; $k \neq j$ (yes=1; else=0)	+
PROFITABLE	Farmer thought PA would be profitable for him/her to use in the future (yes=1; else=0)	+
IMPORTANT	Farmer thought PA would be important in his/her state five years in the future (yes=1; else=0)	+
COTQUALITY	Farmer thought PA would improve lint quality (yes=1; else=0)	+
ENVIQUALITY	Farmer thought PA would improve environmental quality (yes=1; else=0)	+
FARMDEALER	Farmer used farm dealers for PA information (yes=1; else=0)	+

Table 1. Continued.

Variable	Definition	Sign
CONSULTANT	Farmer used crop consultants for PA information (yes=1; else=0)	+
UEXTENSION	Farmer used Extension for PA information (yes=1; else=0)	+
FARMERS	Farmer used other farmers for PA information (yes=1; else=0)	+
TRADESHOW	Farmer used tradeshows for PA information (yes=1; else=0)	+
INTERNET	Farmer used the Internet for PA information (yes=1; else=0)	+
NEWSMEDIA	Farmer used news media for PA information (yes=1; else=0)	+
ALFL	Farm located in Alabama or Florida (yes=1; else=0)	+/–
AR	Farm located in Arkansas (yes=1; else=0)	+/–
GA	Farm located in Georgia (yes=1; else=0)	+/–
LA	Farm located in Louisiana (yes=1; else=0)	+/–
MO	Farm located in Missouri (yes=1; else=0)	+/–
MS	Farm located in Mississippi (yes=1; else=0)	+/–
NC	Farm located in North Carolina (yes=1; else=0)	+/–
SC	Farm located in South Carolina (yes=1; else=0)	+/–
TX[1]	Farm located in Texas (yes=1; else=0)	NA
VA	Farm located in Virginia (yes=1; else=0)	+/–

[1] Reference categories excluded from Tobit regressions.
[2] OTHERS refers to the adoption of at least one of the following PA technologies before or at the same time as PA technology *j*: yield monitors without GPS, management zone soil sampling, soil survey maps, handheld GPS/PDA, COTMAN plant mapping, digitized mapping and/or electrical conductivity.

Walton et al. (2008) and Walton et al. (2010a) hypothesized that household income was positively related to PA adoption (*LOWINCOME* (reference category), *MEDINCOME*, *HIGHINCOME*). Adopters with higher incomes are more likely to have the funds available to invest in a new technology sooner after it becomes commercially available in the market (Rogers, 1983). Also, higher income farmers may have greater access to information about the new technology than lower income farmers, reducing the time from commercialization to adoption (Rogers, 1983). If a farmer adopted other PA technologies in the same year or before adopting a specific PA technology, the farmer was hypothesized to adopt the specific PA technology earlier than those who did not ($YR_k \geq YR_j$; k=YMR, RMS, GSS or OTHERS; *j*=YMR, RMS or GSS; $k \neq j$). For example, if a farmer used GSS for the same or more years than YMR ($YR_{GSS} \geq YR_{YMR}$), the farmer was expected to adopt YMR earlier than farmers who had not used GSS for the same or more years. If farmers had used other PA technologies, they may be more likely to adopt the specific PA technology, given a positive perception of net benefits from using the earlier-adopted PA technologies (Walton et al., 2008).

Four farmer perceptions were expected to influence early adoption. Several studies expected that the farmer's perception about the profitability (*PROFITABLE*) and importance (*IMPORTANT*) of PA in the future had a positive effect on PA adoption (Roberts et al., 2004a, 2004b; Torbett et al., 2007). Farmers who are more optimistic about the future profitability and importance of PA would expect greater future benefits from PA technology adoption and would be more likely to adopt earlier than less optimistic farmers (Torbett et al., 2007). Farmers who reported experiencing improvements in cotton quality through the use of PA technologies (*COTQUALITY*) were hypothesized to adopt PA technologies earlier than others. Farmers who perceive improvements in cotton quality are more likely to experience those improvements after the PA technology was adopted, increasing the likelihood that they would adopt earlier than others. Farmers who reported experiencing improvements in environmental quality through the use of PA technologies (*ENVIQUALITY*) were expected to adopt earlier than those who did not. These farmers were hypothesized to expect improvements after the technology was adopted, increasing the likelihood of earlier adoption (Larkin et al., 2005).

Many researchers hypothesized that farmers who obtain PA information from farm dealers (*FARMDEALER*), crop consultants (*CONSULTANT*), university extension (*UEXTENSION*), other farmers (*FARMERS*), trade shows (*TRADESHOW*), internet (*INTERNET*), and news media (*NEWSMEDIA*) were more likely to adopt PA technologies (Fountas et al., 2005; Velandia et al., 2010). The ability of farmers to make profitable PA adoption decisions increases as they become more informed by using each of these information sources (Walton et al., 2010b), and information availability would influence early adoption.

Binary dummy variables were included to account for potential differences in adoption timing among farmers located in different states (*ALFL*, *GA*, *LA*, *MO*, *MS*, *NC*, *SC*, *TN*, *VA*). Farmers in Florida were combined with farmers in Alabama (*ALFL*) because Florida had too few observations. The reference state was Texas (*TX*), because most cotton farms in the survey were located in Texas. The parameter estimates for these variables estimate differences in the timing of adoption by farmers in those states compared to the timing of adoption by Texas farmers.

RESULTS

The F-statistic for the YMR, RMS and GSS Tobit regressions indicate that the regressions explain the timing of adoption well (Prob > F = 0.0000 in all regressions). The pseudo R^2s are 43%, 36% and 23% for the YR_{YMR}, YR_{RMS} and YR_{GSS} Tobit models, respectively. Variance Inflation Factors (VIF) less than 1.7

provide evidence for the reliability of the hypothesis tests. The significant marginal effects ($\alpha \leq 0.1$) of the explanatory variables are reported in Table 2. The marginal effects indicate the increase (decrease) in YR_j for a one unit increase in an explanatory variable, suggesting earlier (later) adoption for a positive (negative) marginal effect (see equation 2).

Table 2. Significant Marginal Effects of the Explanatory Variable from the Tobit Regressions for the Timing of Yield Monitoring (YMR), Passive Remote Sensing (RMS) and Grid Soils Sampling Adoption (GSS).

	YR_{YMR}	YR_{RMS}	YR_{GSS}
Variable[1]	M. E.[2]	M. E.	M. E.
YIELD	0.056*	...	...
TENURE	...	...	−0.497**
AGE_j	−0.008***	−0.011**	−0.030***
COMPUTER	0.120**	...	0.387***
LAPTOP	0.145**	...	−0.325***
MEDINCOME	0.175***	...	...
HIGHINCOME	0.185***	...	...
$YR_k \geq YR_j$[3]	...	0.776*	−0.571***
$YR_k \geq YR_j$	0.343**	0.538**	...
$YR_k \geq YR_j$	1.013***	3.565***	1.917***
PROFITABLE	0.141***	0.177*	...
IMPORTANCE	0.259***	...	...
ENVIQUALITY	0.181***	...	0.715***
FARMDEALER	−0.093**	...	...
CONSULTANT	−0.095**	−0.313***	0.277**
TRADESHOW	...	0.174*	...
INTERNET	−0.113**	...	−0.277***
NEWSMEDIA	...	0.275**	...
ALFL	...	...	0.384*
AR	...	0.567**	0.431*
LA	...	...	1.350***
MO	...	0.784**	1.340***
MS	...	...	1.568***
NC	...	...	0.362*
SC	...	...	0.634**
TN	...	...	0.988***

[1] Variables are defined in Table 1.
[2] Marginal effects.
[3] k = RMS, GSS and OTHERS, and j = YMR down the YR_{YMR} column; k = YMR, GSS and OTHERS, and j = RMS down the YR_{RMS} column; and k = RMS, YMR and OTHERS, and j = GSS down the YR_{GSS} column.

*, **, *** Significant at the 0.1, 0.05 and 0.01 probability levels, respectively.

Yield Monitor (YMR) Tobit Results

Holding other variables constant, on average the marginal effects in Table 2 indicate that a 405 kg ha^{-1} increase in yield (*YIELD*) increased YR_{YMR} by 0.056 years and a one year increase in age (AGE_{YMR}) decreased YR_{YMR} by 0.008 years. Thus, farmers with higher yields adopted earlier and older farmers adopted later than other farmers. Farmers who used a computer for farm management (*COMPUTER*) used YMR 0.12 years longer (adopted earlier) than those who did not and those who used a laptop/PDA in the field (*LAPTOP*) used YMR 0.145 years longer (adopted earlier) than other farmers. Farmers with annual incomes between $100,000 and $199,999 (*MEDINCOME*) and those with annual incomes greater than $200,000 (*HIGHINCOME*) used YMR 0.175 and 0.185 years longer (adopted earlier), respectively, than those with incomes less than $100,000. Farmers who adopted GSS ($YR_{GSS} \geq YR_{YMR}$) and other PA technologies ($YR_{OTHERS} \geq YR_{YMR}$) before or at the same time as YMR used YMR 0.343 and 1.013 years longer (adopted earlier), respectively, than those who began using PA technologies with the adoption of YMR. Farmers who thought PA would be profitable (*PROFITABLE*) and important (*IMPORTANT*) in the future and thought PA provided improvements in environmental quality (*ENVIQUALITY*) used YMR 0.141, 0.259 and 0.181 years longer (adopted earlier), respectively, than those who did not. Lastly, obtaining PA information from farm dealers (*FARMDEALER*), consultants (*CONSULTANT*) or the Internet (*INTERNET*) reduced YR_{YMR} by 0.093 years, 0.095 years and 0.113 years, respectively, suggesting these farmers adopted YMR later than others.

Passive Remote Sensing (RMS) Tobit Results

A one year increase in age (AGE_{RMS}) reduced YR_{RMS} by 0.011 years, suggesting older farmers adopted later than younger farmers. Farmers who began practicing PA by adopting YMR ($YR_{YMR} \geq YR_{RMS}$), GSS ($YR_{GSS} \geq YR_{RMS}$) or other PA technologies ($YR_{OTHERS} \geq YR_{RMS}$) at the same time or before adopting RMS used RMS 0.776, 0.538 and 3.565 years longer than those who began practicing PA with the adoption of RMS. Thus, farmers who had adopted other PA technologies were more likely to adopt RMS earlier than those who had not adopted other PA technologies. Farmers who thought PA would be profitable in the future (*PROFITABLE*) used RMS 0.177 years longer (adopted earlier) than other farmers. Obtaining information from trade shows (*TRADESHOW*) or news media (*NEWSMEDIA*) increased YR_{RMS} by 0.174 and 0.275 years (earlier adoption), respectively, while obtaining information from consultants (*CONSULTANT*) reduced YR_{RMS} by 0.313 years (later adoption) compare with other farmers. Farmers in Arkansas (*AR*) and Missouri (*MO*) adopted RMS 0.567 and 0.784 years earlier than Texas farmers (Table 2).

Grid Soil Sampling (GSS) Tobit Results

An increase of 0.1 in the ratio of land rented to total land farmed (*TENURE*) reduced YR_{GSS} by 0.05 years, and a one year increase in age (AGE_{GSS}) reduced YR_{GSS} by 0.03 years; thus farmers with more rented land and older farmers adopted later than other farmers. Use of a computer for farm management (*COMPUTER*) increased YR_{GSS} by 0.387 years (earlier adoption), while use of a laptop/PDA in the field (*LAPTOP*) reduced YR_{GSS} by 0.325 years (later adoption). Farmers who adopted YMR at the same time or before adopting GSS ($YR_{YMR}\geq YR_{GSS}$) used GSS 0.571 fewer years (adopted later) than other farmers, while those who adopted other PA technologies before or at the same time as GSS ($YR_{OTHERS}\geq YR_{GSS}$) used GSS 1.971 years longer (adopted earlier) than others. Farmers who thought PA would improve environmental quality (*ENVIQUALITY*) used GSS 0.715 longer (adopted earlier) than other farmers. Farmers who used consultants (*CONSULTANT*) to obtain PA information used GSS 0.277 years longer (adopted earlier) than others, while those who used the Internet (*INTERNET*) used GSS 0.277 fewer years (adopted later) than others. Farmers in all states except Georgia and Virginia used GSS longer than farmers in Texas (Table 2), suggesting they adopted earlier than Texas farmers.

SUMMARY AND CONCLUSION

This study evaluated factors influencing the timing of PA technology adoption. Three Tobit models were used to estimate the factors affecting the number of years farmers had used YMR, RMS and GSS adoption. In this context, if a farmer used a PA technology more years, the farmer had adopted it earlier than a farmer who used the technology fewer years. The results for YMR suggest that younger cotton farmers who had higher yields, thought PA would be profitable and important in the future, thought PA would improve environmental quality, used a computer for farm management and a laptop in the field, had annual taxable household income of $100,000 or more, and adopted GSS and other PA technologies before or in the same year as YMR were more likely to adopt YMR earlier than other farmers. Farmers who obtained PA information from farm dealers, consultants or the Internet adopted YMR later than others.

The regression results for RMS suggest that younger farmers in Arkansas and Missouri, who adopted YMR, GSS and other PA technologies before or at the same time as RMS, thought PA would be profitable in the future and relied on tradeshows and the news media for PA information adopted RMS earlier than others. Those who relied on PA information from consultants adopted RMS later than others.

Results from the GSS Tobit regression suggest that younger farmers who owned more of the land they farmed, used a computer for farm management, adopted other PA technologies before or at the same time as GSS, thought PA would improve environmental quality, and relied on PA information from consultants adopted GSS earlier than others. Farmers with farms in Georgia, Virginia and Texas, who adopted YMR before or at the same time as GSS, used a laptop/PDA in the field and relied on the Internet for PA information adopted GSS later than others.

Results from this study will be useful for researchers, agricultural support personnel, machinery manufacturers and agricultural retailers by providing improved information about why farmers adopt PA technologies when they do. Given the potential benefits of PA, earlier adoption may help farmers improve field efficiency of inputs, increase profits, and decrease negative environmental impacts sooner than without the information. Additionally, the results can be used by scientists and researchers to put PA technology adoption and diffusion into a historical perspective for future research (Griffin et al., 2010). Lastly, machinery manufacturers and agricultural retailers might use the results from this study to anticipate future demand for PA technologies (Fountas et al. 2005).

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