Intensity of Precision Agriculture Technology Adoption by Cotton Producers

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Many studies on the adoption of precision technologies have generally used logit models to explain the adoption behavior of individuals. This study investigates factors affecting the intensity of precision agriculture technologies adopted by cotton farmers. Particular attention is given to the role of spatial yield variability on the number of precision farming technologies adopted, using a count data estimation procedure and farm-level data. Results indicate that farmers with more within-field yield variability adopted a higher number of precision agriculture technologies. Younger and better educated producers and the number of precision agriculture technologies used were significantly correlated. Finally, farmers using computers for management decisions also adopted a higher number of precision agriculture technologies.

Key Words: precision technologies, Poisson, negative binomial count data method, GPS, education, cotton

Precision agriculture (PA) or precision farming (PF) generally refers to a system that assesses within-field variability in soil and crops. Information gathered in these assessments is then used to develop site-specific management practices to optimize crop production. A wide variety of technologies is used in collecting site-specific data and deploying site-specific management practices. Some of these technologies have been commercially available since the late 1980s, including yield monitoring/mapping, variable rate application, and a host of other spatial management technologies. The adoption of precision agriculture technologies is somewhat different from many other technologies introduced in agricultural production. A major difference is the fact that precision agriculture technologies consist of a complex set of technologies, each with a specific purpose (Lowenberg-DeBoer 1998, Khanna, Epouhe, and Hornbaker 1999, Khanna 2001). Therefore, farmers may adopt one or more technologies and evaluate those before adopting additional technologies (Byerlee and de Polanco 1986, Leathers and Smale 1991). The most recent studies have examined the adoption of several specific technologies (Daberkow, Fernandez-Cornejo, and Padgitt 2002, Daberkow and McBride 2000, Fountas et al. 2003, Griffin et al. 2004, Fountas et al. 2005, Blackmore et al. 2006, Walton et al. 2008, Walton et al. 2010).

The adoption of PA technology in cotton production has been somewhat different than in grain crops, because cotton yield monitors were not available until the late 1990s, while yield moni-

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tors for combines were introduced in the late 1980s (Griffin et al. 2004). The unavailability of yield monitors influenced cotton producers to use grid soil sampling or other soil mapping techniques as an entry point for other precision agriculture technologies (Walton et al. 2008). Since the introduction of the cotton yield monitor, several studies have examined the adoption of precision agriculture technologies in cotton production (Roberts et al. 2004, Banerjee et al 2008, Larson et al. 2008, Walton et al. 2008, Walton et al. 2010). Most of these studies estimate the likelihood of adoption using logit or probit regression.

In 2005 Mishra and Park used the count data method to study the number of Internet applications adopted by farmers in the United States (Mishra and Park 2005). Their thinking was that farmers and their households adopt the Internet and use it for various reasons (e.g., forward contracting, paying bills, obtaining loans, or contact with advisory services). Similarly, farmers adopting PA technologies may not be limited to adopting only one technology, but may be inclined to adopt more once they are experienced and feel comfortable with one technology. The present study is unique in determining the influence of various farm, operator, and location attributes on the intensity (number) of precision farming technologies adopted by farmers. Particular attention is given to the role of spatial yield variability. The technologies evaluated include yield mapping, variable rate application, yield monitoring, grid sampling, and others. Precision farming is characterized by a number of component technologies which can be adopted in sets by the farm operator. Hence, some farm operators may adopt one or fewer components and others may adopt several or many components. If the adoption intensity or frequency (dependent variable) is measured as the number of precision farming technologies adopted by farm operators, observations on the dependent variable are represented by non-negative integer quantities, and failure to account for the integer nature of the data could bias results and policy prescription (Haab and McConnell 1996). Information on the number of PA technologies adopted by farm operators is critical to (i) the development of educational programs about precision agriculture, and (ii) anticipation of future demand for PA innovations by cotton producers, crop consultants, dealerships, and equipment manufacturers.

Literature Review

Precision agriculture (PA) is an approach to reorganizing the total system of agriculture production towards one that optimizes input use over space (Roberts, English, and Mahajanashetti 2000). The early literature provides broad agreement that profitability and/or input cost reduction from innovation or technology adoption plays a key role in the extent and rate of technology adoption (Feder, Just, and Zilberman 1985, Rogers 1995). In 1997, Whelan, McBratney, and Boydell (1997) concluded that the desire to respond to production variability on a fine-scale has become the goal of precision agriculture. Swinton and Lowenberg-DeBoer (1998) conclude that because precision farming practices are site-specific, profitability potential is also site-specific. In a follow-up study, Lowenberg-DeBoer (1999) showed that site-specific farming, to which most of PA technologies are geared, could reduce whole-field yield variability. Finally, Zhang, Wang, and Wang (2002), while assessing the role of precision agriculture throughout the world, concluded that the success of precision agriculture technologies will have to be measured by economic and environmental gains.

It has long been recognized that the advancement of PA management depends on the emergence and convergence of several technologies (Shibusawa 1998), including geographic information systems (GIS), Global Positioning System (GPS), in-field remote sensing, automatic controls, miniaturized computer components, mobile computing, and telecommunications (Gibbons 2000). Lowenberg-DeBoer and Erickson (2000) conclude that yield monitors, GPS receivers, and GIS mapping are useful for maintaining accurate records of the location, planted acres, and yield of crops. In 2002, Cox reviewed developments in information technology that are contributing to global improvements in crop and livestock production (Cox 2002). In a case study of six leading early adopters of precision agriculture technologies, Batte and Arnholt (2003) point out that precision farming has the potential to help farmers improve input allocation decisions. The specific role of GIS and GPS in precision farming was explored by Nemenyi et al. (2003), who concluded that GIS maps created by complex computing algorithms can improve the effectiveness of agrotechnological decisions.

While both the potential for PA to improve sustainability (fiscal and environmental) and the need for continuing advancements in a suite of technology are critical factors to the ultimate success of this farming approach, understanding the behavior of individual farmers adopting new technologies is also important. To that end, Roberts, English, and Mahajanashetti (2000) found that the profitability of precision farming—as assessed by cotton farmers with varying degrees of adopting a suite of technologies—depends immensely on the degree of spatial variability of soil attributes and yield response. In studying adoption of PA technologies in the United States, Daberkow and McBride (2003) found that farm size, human capital, risk preference, off-farm labor supply, location, and tenure are some of the factors that affect adoption. With respect to human capital (or knowledge capital) in particular, Daberkow and McBride (2003) also noted that human capital could take the form of familiarity with related technologies. The authors show that farmers who kept computerized financial records were more likely associated with PA technologies.

In this study we advance the literature related to PA adoption by focusing on spatial yield variability and how that farm characteristic corresponds with the number of PA technologies adopted. The focus on explaining the number of PA technologies is new to the adoption literature and is ideally suited to this case study, which uses a sample of cotton farmers in the southern United States. This is because the production of cotton can employ a sufficient number of technologies to support the empirical analysis.

Empirical Approach

In some cases, such as number of patents (Cincera 1997), visits to doctors (Cameron and Trivedi 2009), and number of foreign domestic investment firms (Gopinath and Vasavada 1999), the count is the variable of ultimate interest. In other cases, such as medical expenditures (Cameron and Trivedi 2009), the variable of ultimate interest is the continuous variable. In our case, the variable of interest is the intensity of adoption, and the number of precision technologies is used as a proxy measure for this variable since it is the best available measure of intensity (which cannot be directly measured). Cameron and Trivedi (2006) point out that in such cases count data models are appropriate. To analyze the effects of various farm, operator, and regional characteristics on the number of precision technologies (such as yield monitors with GPS, yield monitors without GPS, soil sampling grid, soil sampling zone, aerial photos, satellite images, soil survey maps, and handheld GPS/PDAs), we use the method employed in patent literature (e.g., Hausman, Hall, and Griliches 1984, Cameron and Trivedi 1986, Cincera 1997).

In this study, the number of precision technologies adopted by a cotton farmer is a function of a set of independent variables ($\mathbf{X}_i$):

$$\ln(\lambda_i) = \alpha_0 + \beta' X_i , \tag{1}$$

where λ_i is the number of precision technologies adopted by farm operator i. Data on the number of precision technologies used constitute a non-negative, integer-valued, random variable. Several authors (e.g., Hausman, Hall, and Griliches 1984, Cameron and Trivedi 1986, Cincera 1997) have presented and discussed count data models as an alternative method to the classical linear model.[1] In the count data models, the primary variables of interest are event counts. We consider the Poisson and the negative binomial distributions, which belong to the linear exponential family, for analyzing the number of precision technologies used by farm operators. We briefly describe the Poisson and negative binomial models below.

Poisson Model

Let Y_i be the observed event count (number of precision technologies used) for the ith farm operator. The Y_i are assumed to be independent and Poisson-distributed. The parameters β depend on a set of explanatory variables (X_i), which are hypothesized to affect the number of precision technologies used by a farm operator:

$$E\left(Y_i \mid X_i\right) = \lambda_i = \exp\left(\beta' X_i\right), \quad i = 1 \ldots N, \tag{2}$$

where λ_i is the intensity-of-rate parameter when referring to the Poison distribution as $p\,[\lambda_i]$. Equa-

[1] See Winkelmann and Zimmermann (1995) for an overview of count data models.

tion (2) is the conditional mean. The probability density function for the Poisson model is

$$(3) \qquad \Pr\left(Y_i = y\right) = f\left(Y_i\right) = \left[\frac{e^{-\lambda_i}\lambda_i^{Y_i}}{Y_i\,!}\right], \quad Y_i = 0,1,2....$$

The first two moments of $p[\lambda_i]$ are $E[Y] = \lambda$ and $V[Y] = \lambda$; the Poisson specification assumes equal mean and variance. Overdispersion (e.g., where the conditional mean and variance are unequal) is qualitatively similar to failure of the homoscedasticity assumption in the linear regression model.

The Negative Binomial Model

A drawback to the Poisson specification is the assumption of equal mean and variance of Y_i, a testable hypothesis. In the negative binomial model, which is more flexible than the Poisson, λ_i is assumed to follow a gamma distribution with parameters (γ, δ), where $\gamma = \exp(\beta' X)$ and δ is common across farmers. The gamma distribution ($\Gamma[\cdot]$) for λ_i is integrated by parts to obtain

$$(4) \quad \Pr\left(Y_i\right) = \int_0^{\infty} \frac{1}{Y_i\,!}\, e^{-\lambda_i}\lambda_i^{Y_i} \mathrm{f}\left(\lambda_i\right) d\lambda_i = \frac{\Gamma\left(\gamma_i + Y_i\right)}{\Gamma\left(\gamma_i\right)\Gamma\left(Y_i + 1\right)}\left(\frac{\delta}{\delta + 1}\right)^{\gamma_i}\left(1 + \delta\right)^{-Y_i},$$

which is a negative binomial distribution with parameters (γ_i, δ). The above framework suggests that the number of precision technologies used by a cotton producer is expressed as a function of various farm, operator, household, and regional characteristics. Specifically, $\lambda_i = \exp(\beta' X_i)$, where X_i is a set of explanatory variables, including age and education of the operator, farming experience, farm size, yield index, and state dummies. A subsequent question then arises as to which model (Poisson or negative binomial) is more appropriate. Cameron and Trivedi (2009) proposed a number of tests for the overdispersion or underdispersion in the Poisson regression model. They test the underlying assumption of mean-variance equality, where the null hypothesis, H_1: $\mathrm{Var}(Y_i) = \mu_i$, is compared with the alternative hypothesis, H_1: $\mathrm{Var}(Y_i) = \mu_i + \alpha^* g(\mu_i)$. The function $g(.)$ is a specified function that maps from R^+ to R^-. Tests for overdispersion or underdispersion are tests of whether $\alpha = 0$.[2] We use a similar test in our study. The marginal effect of a change in an independent variable on the conditional mean of the dependent variable was calculated using STATA software. Cameron and Trivedi (2009, pp. 562–566) provide a detailed explanation and interpretation of marginal effects of the Poisson and negative binomial models. Specifically, they point out that the marginal effect of the ith continuous variable is $(ME_i) = E(y|x) \cdot \beta_i$. For discrete variables, the exponentiated coefficient is the change in conditional mean for individuals with a given characteristic.

The choice of attributes associated with the number of precision technologies used is guided by human capital theory, farm and production characteristics, and other adoption models. Nelson and Phelps (1980), Khaldi (1979), and Wozniak (1989) use education as a measure of human capital to reflect the ability to innovate (either technology or insurance). In addition, other factors affecting the adoption of precision farming technologies are guided by the literature (Feder, Just, and Zilberman 1985, Rogers 1995, Daberkow and McBride 2003). In our model, we use financial, location, and physical attributes of the farm firm that may also influence profitability and, ultimately, the adoption of precision agriculture technologies (Daberkow and McBride 2003).

Measuring Field Spatial Variability

To measure field spatial variability, we follow Larson and Roberts' (2004) method, with a slight modification.[3] Specifically, field spatial variability (FSV) for crop i is calculated using the following variance formula:

$$(5) \quad FSV_i = 0.5\left(Y_{\text{low}} - Y_{\text{avg}}\right)^2 + 0.5\left(Y_{\text{high}} - Y_{\text{avg}}\right)^2,$$

where Y_{low} and Y_{high} is the estimated yield of the least and most productive of the typical field, and Y_{avg} is the estimated average yield for the typical

[2] Tests for overdispersion and underdispersion are important. Failure has consequences similar to those of heteroskedasticity in a linear regression model (Cameron and Trivedi 1990). The test of overdispersion was estimated using the STATA software package.

[3] An anonymous reviewer pointed out this modification.

field. Note that each part is given equal weight. Finally, the coefficient of the field spatial yield variability ($CVFSV_i$) [4] statistic is calculated using the following formula:

$$(6) \qquad CVFSV_i = \frac{FSV_i^{0.5}}{Y_{avg}} \times 100.$$

All the relevant information on the field yield was collected through a survey and the information was used to calculate field spatial variability. In particular, farmers were asked: "Since yields are likely to vary within field, please estimate your cotton lint yield (lb/acre) for the following portions of your cotton field: (1) least productive 1/3; (2) average productive 1/3; and (3) most productive 1/3."

Data

Data for this study were obtained from a survey of cotton producers in the southeastern part of the United States (Alabama, Arkansas, Florida, Georgia, Louisiana, Mississippi, Missouri, North Carolina, South Carolina, Tennessee, and Virginia). The survey used a questionnaire to obtain information about producer attitudes toward and use of precision agriculture technologies. Following Dillman's (1978) general mail survey procedures, the questionnaire, a postage-paid return envelope, and a cover letter were sent to each producer. A reminder post card was sent one week after the initial mailing. Three weeks later a second mailing was sent to those who had not responded to the original mailing and reminder. The mailing list of potential cotton producers for the 2003–04 crop year was obtained from the Cotton Board in Memphis, Tennessee. The survey was mailed in January and February of 2005. Of the 12,245 questionnaires mailed, 18 were returned as undeliverable, 184 respondents were no longer cotton producers, and 1,215 respondents provided useable information, for a response rate of 10 percent. However, due to missing information on some variables, only 892 observations were used in this study. Figure 1 provides information about the distribution of the number of precision technologies adopted by cotton farmers in 2003–04. About 39 percent of farmers reported using one or more precision technologies; additionally, about 9 percent of cotton farmers used three or more precision technologies.

The 2005 Southern Precision Farming Survey collected information on the demographics of cotton farmers (such as age of the operator, years of farming experience, highest educational attainment) and cotton farming. Farmers were also asked about their production practices, including acres planted, rented acres, and input use. On the issue of income farmers were queried on the percentage of household income received from farming. Farmers were also asked to provide the best statement that described their farm planning goals.[5] In this study we used a dummy variable to assess the impact of future farm size expansion on the number of precision technologies adopted by cotton farmers. Farmers were asked if they used a computer for farm management. Studies on adoption of computers by farmers indicate that farmers who adopted computers are more likely to adopt newer technology and computers with Internet connection (Mishra and Park 2005). We use a dummy variable—whether or not the farmer used computers for farm management—to assess the impact of computer use on the number of precision technologies adopted by cotton farmers.

The 2005 Southern Precision Farming Survey queried farmers on 10 possible technologies. Cotton farmers were asked if they used and the number of years they had used the following information-gathering technologies: (i) yield monitor—with GPS, (ii) yield monitor—no GPS, (iii) soil sampling—grid, (iv) soil sampling—zone, (v) aerial photos, (vi) satellite images, (vii) soil survey maps, (viii) handheld GPS/PDA devices, (ix) COTMAN plant mapping, and (x) digitized mapping. The sum of the number of information-gathering technologies reported by the farmer was used as the dependent variable. Finally, the 2005 Southern Precision Farming Survey asked farmers about their perceptions of the future profitability of precision agriculture. Specifically,

[4] The log of spatial yield variability is used to scale down the variable.

[5] Specifically, farmers were asked to check one statement that best describes their farm planning goals: (i) I want to acquire enough farm assets to generate sufficient income for family living, (ii) I want to expand the size of operation through acquiring additional resources, (iii) I am thinking about retirement and the transfer of my farm to the next generation, or (iv) I am considering selling the farm and moving to a different career.

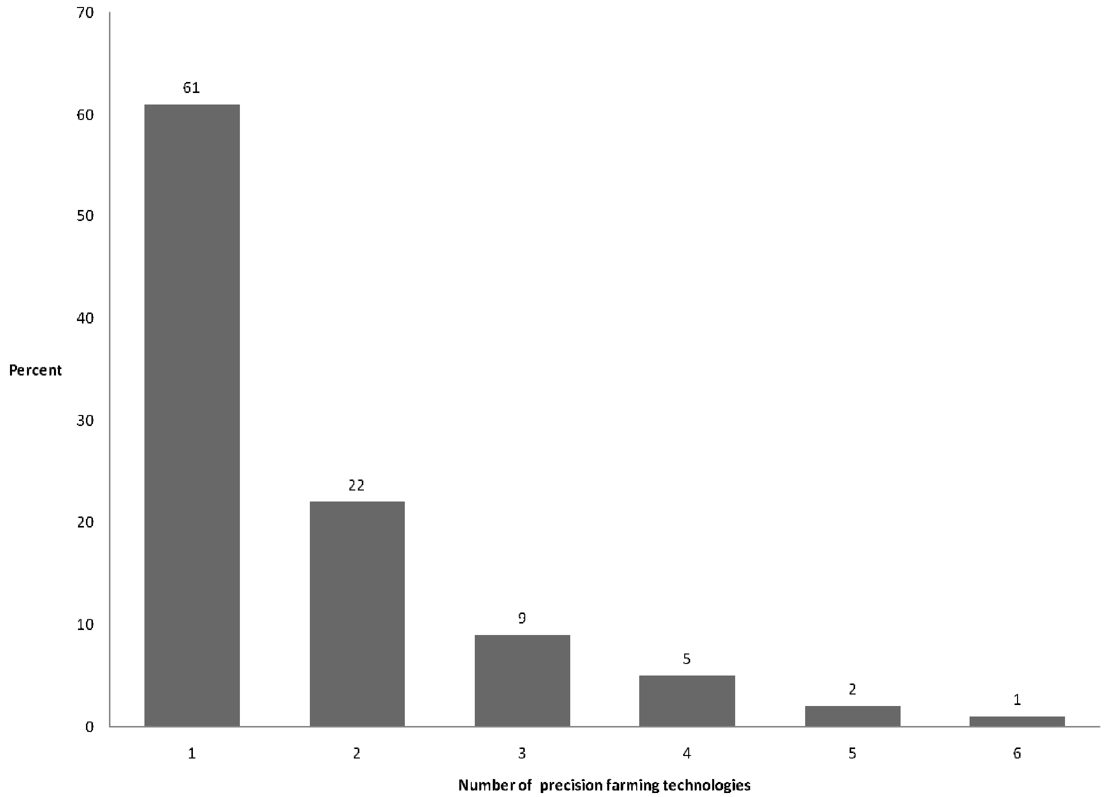

Figure 1. Distribution of Number of Precision Technologies by Cotton Farmers in the Southern United States

farmers were asked (1=yes, and 0=no) if they thought it would be profitable for them to use precision farming technologies in the future. Results in Table 1 show that about 54 percent of the farmers in the sample believed that it would be profitable for them to use precision farming technologies in the future.

Table 1 provides definitions and summary statistics for the variables used in the empirical model. The average cotton farmer in the sample is 49 years of age and has 14 years of schooling. An average cotton farmer in the sample has about 26 years of farming experience and receives 73 percent of household income from farming. The modal cotton precision farmer used one precision technology (Figure 1), while average precision technology use was 0.85 (Table 1). Additionally, 54 percent of cotton farmers thought precision technologies would be profitable in the near future. About 18 percent of the farms were located in Georgia or North Carolina, compared to 13 and 12 percent in Mississippi and Alabama, respectively. Arkansas was used as the reference state in the regression.

Results

First the choice of a Poisson and negative binomial model was tested; results indicated that the null hypothesis of equal mean and variance was rejected. The overdispersion test statistic was significant at the 1 percent level (Table 2, last row). Table 2 therefore presents only the estimates from the negative binomial model and their marginal effects. The estimated model fits reasonably well, as indicated by the 70 percent correlation between observed and predicted values (Table 2). In the interest of brevity and because of the rejection of the Poisson model, we will present results of only the negative binomial model.

Results suggest that an additional year of age (*OP_AGE*) is associated with, on average, one fewer precision technology adopted by farmers

Table 1. Definition of Variables and Summary Statistics

Variable	Definition	Means (Std. dev.)
NUMTECH	Number of precision technologies adopted	0.85 (1.204)
OP_AGE	Age of farm operator (*years*)	49.29 (11.275)
F_EXPERIENCE	Farming experience (*years*)	25.81 (11.443)
OP_EDUC	Formal education of farm operator (*years*)	14.36 (2.196)
COMPFARM	= 1 if farmer uses computer for farm management	0.58 (0.492)
SHARE_RENTED	Percentage of rented acres in total operated acres	65.81 (33.772)
FARMPLAN	= 1 if the farm operator is planning to expand size of the operation or acquire assets to generate additional income	0.72 (0.446)
FUTURE_ADOPT	= 1 if the farm operator thinks it would be profitable to use precision technologies in the future	0.54 (0.498)
F_INCOME	Percentage of farm income in total household income	73.08 (27.814)
CVFSV	Log field spatial yield variability	3.42 (0.540)
S_ALABAMA	Dummy variable, = 1 if state is Alabama	0.12 (0.321)
S_NR_CAROLINA	Dummy variable, = 1 if state is North Carolina	0.18 (0.383)
S_FLORIDA	Dummy variable, = 1 if state is Florida	0.02 (0.133)
S_GEORGIA	Dummy variable, = 1 if state is Georgia	0.18 (0.381)
S_MISSISSIPPI	Dummy variable, = 1 if state is Mississippi	0.13 (0.339)
S_LOUISIANA	Dummy variable, = 1 if state is Louisiana	0.07 (0.258)
S_SO_CAROLINA	Dummy variable, = 1 if state is South Carolina	0.06 (0.238)
S_MISSOURI	Dummy variable, = 1 if state is Missouri	0.03 (0.181)
S_TENNESSEE	Dummy variable, = 1 if state is Tennessee	0.09 (0.280)
S_VIRGINA	Dummy variable, = 1 if state is Virginia	0.03 (0.171)
Sample	892	

Source: 2005 Southern Precision Farming Survey.

(Table 2, column 3).[6] This finding is consistent with the adoption literature (Feder, Just, and Zilberman 1985, Daberkow and McBride 2003) and with the hypothesis that older farmers are less likely to adopt new technologies because of a lower expected payoff from a shortened planning horizon over which benefits can accumulate. Results suggest that educational attainment (*OP_EDUC*) positively influences the number of precision technologies adopted (Table 2). An addi-

[6] Cameron and Trivedi (2009) show that another way of interpreting the marginal effect of discrete variables is to exponentiate the coefficients (e^{β}). One additional year in age is associated with the number of PA technologies decreasing by 1.02. The exponentiated coefficient of discrete variables applies to any Maximum Likelihood estimation (see Cameron and Trivedi 2009, pages 558–564).

Table 2. Parameter Estimates of Factors Affecting Number of Precision Farming Tools by Cotton Farmers in the Southern United States

Variable	Negative Binomial Model Parameter Estimates [a]	Marginal Effect [b]
Intercept	-2.352*** (0.678)	--
Age of the operator	-0.017** (0.008)	-0.014**
Operator's educational attainment	0.093*** (0.022)	0.079***
Farming experience	0.001 (0.008)	0.001
Use computers for farm management	0.554*** (0.109)	0.425***
Share of total operated acres rented	-0.001 (0.001)	-0.002
Farm expansion	-0.233** (0.108)	-0.211**
Future adoption of precision technologies	0.529*** (0.104)	0.416***
Percentage of farm income in total household income	0.002** (0.001)	0.002**
Log field spatial yield variability	0.077** (0.013)	0.068**
Alabama, dummy variable	0.077 (0.195)	0.068
North Carolina, dummy variable	0.031 (0.179)	0.034
Florida, dummy variable	-0.709* (0.429)	-0.437**
Georgia, dummy variable	0.006 (0.184)	0.006
Mississippi, dummy variable	0.509*** (0.181)	0.522***
Louisiana, dummy variable	0.276 (0.213)	0.266
South Carolina, dummy variable	0.344 (0.238)	0.344
Missouri, dummy variable	0.472** (0.249)	0.507**
Tennessee, dummy variable	0.104 (0.202)	0.092
Virginia, dummy variable	0.105 (0.299)	0.094
Wald chi square	199.20***	
Correlation between observed and predicted	70.01	
Log-likelihood	-970.179	
Overdispersion test	33.20***	

[a] Numbers in parentheses are standard errors. Significance at the 10 percent, 5 percent, and 1 percent levels are indicated by single, double, and triple asterisks, respectively. The coefficient here can be interpreted as semi-elasticity and is calculated using information from Cameron and Trivedi (2009, p. 562).

[b] Marginal effect is calculated at the mean of the dependent variable. The marginal effect for discrete variables is estimated as $e^{\hat{\beta}}$. The marginal effect of a unit change in a continuous variable regressor, x_j, equals $\partial E(y|x)/\partial x_j = \beta_j \exp(x'\beta)$ (see Cameron and Trivedi 2009, p. 562).

tional year of schooling is associated with an 0.08 additional number of PA technologies. A plausible explanation is that many educated farmers are young and, it is often hypothesized, more willing to innovate and adopt new technologies that reduce time spent farming (Mishra et al. 2002). In particular, Mishra et al. (2002) point out that many young farmers are more educated and often have off-farm jobs. Our results are also consistent with the findings of Daberkow and McBride (2003), who investigated the impact of education, in addition to other factors, on PA technology adoption.

Mishra, El-Osta, and Johnson (1999) concluded that cash grain farmers who kept computerized financial records were more likely to be successful. Computer use for financial record keeping may also be an indicator of preferences toward using information technology tools for farm management. Results in Table 2 indicate that farmers who use computers for farm management[7] will have, on average, about 0.42 more PA technologies than their counterpart.

The 2005 cotton survey queried farmers on farm planning. In particular, farmers were asked if they planned to expand the size of their operation or acquire additional assets to generate additional income (*FARMPLAN*); 72 percent responded positively. Results in Table 2 show that cotton farmers who planned to expand their operations were likely to use (on the margin) 0.21 fewer PA technologies than their counterpart. A possible explanation is that farmers planning to expand their operations may use their resources (particularly income and labor) to purchase additional land rather than investing it in an additional PA technology. Future expectation of increased profits through precision technologies (*FUTURE_ADOPT*) was, *ceteris paribus,* positively correlated with the number of precision technologies adopted by cotton farmers. The results suggest that farmers who thought precision technologies would be profitable in the future adopted, on average, more precision technologies than farmers who thought PA technologies would not be profitable (marginal effect = 0.42). Mishra et al. (2002) used share of farm income in total household income as a measure of farm size. They concluded that the share of farm income in total household income was higher for large farms whose operators indicated farming as their main occupation. Further, Mishra et al. (2002) argued that a lower percentage of household income earned from farming implies that more household labor is employed off the farm, and that less household labor is available to evaluate and implement new technologies. We use share of farm income in total household income (*F_INCOME*) as a variable in the model to assess the impact of farm size and/or the importance of farming to the household. Recall that, on average, households derived 73 percent of their total income from farming (Table 1). The results in Table 2 suggest that a 1 percent increase in farm income increases the number of PA technologies adopted by farmers by 0.1 percent. This result is consistent with the trade-off between on-farm and off-farm labor requirements.

An important finding from this study is that spatial yield variability (*LN_CVFSV*) has a positive impact on the number of PA technologies adopted by cotton farmers. The marginal effect suggests that a 1 percent increase in spatial yield variability was associated with 0.06 additional PA technologies being adopted by cotton farmers in the South. The climatic, soil, water, and topographical characteristics of geographic areas tend to constrain the number and types of crops and livestock that can be grown or raised. County clusters in a state, based on types of commodity produced, have shown a tendency for a select few commodities to dominate the production landscape for geographic areas that cut across traditional political boundaries. Since we are investigating cotton farmers in the Southeast, we include state dummy variables to assess the impact of location on adoption of PA technologies. Results in Table 2 suggest that location of farms plays an important role in the number of PA technologies adopted by cotton farmers. In particular, cotton farmers in Mississippi are likely to adopt 0.52 additional PA technologies when compared to farmers in the benchmark state of Arkansas (Table 2).[8] Simi-

[7] Potential endogeneity of this variable was tested using Hausman's test. Based on the statistics, the null hypothesis of endogeneity was rejected.

[8] Statistical tests (t-test and Wald test) show that the coefficients on state dummies for Mississippi, Missouri, and Florida are statistically significant at the 5 percent level of significance. However, the Wald test also shows that the coefficients on state dummies for Mississippi and Missouri are not statistically different from one another.

larly, farmers in Missouri adopt about 0.51 additional PA technologies when compared to farmers in the benchmark state of Arkansas. However, a Wald test on the coefficient shows that Mississippi and Missouri are not different from one another. A plausible explanation is that survey respondents from Mississippi and Missouri were younger and had more years of education than respondents from Arkansas. On average, survey respondents from Mississippi and Missouri were 1.4 years younger and had 1.5 more years of education than those from Arkansas. On the other hand, cotton farmers in Florida would adopt 0.44 fewer PA technologies compared to farmers in the benchmark state of Arkansas—consistent with the fact that both climate and soils are not very supportive of cotton production in much of Florida. Additionally, the Florida cotton crop is primarily dryland, so yield levels are considerably lower than in Arkansas.

Conclusions

This study examined the effects of various farm, operator, and regional characteristics on the intensity (number) of precision agriculture technologies adopted by cotton farmers in the Southeast. A negative binomial count model was used to analyze data collected through a 2005 survey of cotton producers in the southeastern United States. This study contributes to the literature in two ways. First, it uses a count data estimation procedure to examine the impact of various factors on the number of precision agriculture technologies adopted by cotton farm operators. Second, it incorporates a measure of within-field yield variability as a factor influencing the number of technologies adopted.

Results from this study suggest that the number of precision agriculture technologies employed by producers is positively correlated with the educational level of the producer and negatively correlated with operator age. These results suggest that younger, better educated producers adopt a larger number of precision agriculture technologies. Farmers using computers for management decisions also adopted a larger number of precision agriculture technologies. These results suggest that targeting these groups for educational programs could increase the probability of success for those programs. Results of this analysis demonstrated that farmers with more within-field yield variability adopted a larger number of precision agriculture technologies. Within-field yield variability has long been thought of as the primary driver of precision agriculture adoption.

Results of this study also reconfirm this long-held belief. Overall, the findings here help identify groups of cotton producers that are more likely to be responsive to precision agriculture technology educational programs. These results also identify those groups where educational programs may be used to expand precision agriculture technology adoption. For example, the marketing efforts of agribusiness firms promoting precision agriculture technologies might benefit from tailoring efforts towards younger farmers more reliant on income generated from farming activities (typically, larger farms) in their efforts to promote precision agriculture technologies. As is well known, soil sampling is often viewed as an entry-level technology into a broader array of PA technologies, and grid and zone soil sampling is the foundation on which yield variability is documented. Grid soil sampling with GPS provides an even finer resolution of the inherent variability of fields. Marketing efforts of local agribusinesses providing soil sampling services might benefit in the medium run, in terms of marketing additional PA accessories, from promotional programs offering package services that offer customized field variability profiles. Likewise, expansion of soil sampling services offered by Extension could also create demand for adoption of integrated precision agriculture systems.

References

Banerjee, S., S.W. Martin, R.K. Roberts, S.L. Larkin, J.A. Larson, K.W. Paxton, B.C. English, M.C. Marra, and J.M. Reeves. 2008. "A Binary Logit Estimation of Factors Affecting Adoption of GPS Guidance Systems by Cotton Producers." *Journal of Agricultural and Applied Economics* 40(1): 335–344.

Batte, M., and M.W. Arnholt. 2003. "Precision Farming Adoption and Use in Ohio: Case Studies of Six Leading-Edge Adopters." *Computers and Electronics in Agriculture* 38(2): 125–129.

Blackmore, S., H.W. Griepentrog, S.M. Pedersen, and S. Fountas. 2006. "The Current Status of Precision Farming in Europe." In A. Srinivasan, ed., *Handbook of Precision Agriculture: Principles and Applications*. Binghamton, NY: The Haworth Press.

Byerlee, D., and E. Hesse de Polanco. 1986. "Farmers' Stepwise Adoption of Technological Packages: Evidence from the Mexican Altiplano." *American Journal of Agricultural Economics* 68(3): 519–527.

Cameron, A., and P. Trivedi. 1986. "Econometric Models Based on Count Data: A Comparison and Implications of Some Estimators and Tests." *Journal of Applied Econometrics* 1(1): 29–53.

____. 1990. "Regression Based Tests for Overdispersion in Poisson Model." *Journal of Econometrics* 46(1): 347–364.

____. 2006. *Microeconometrics: Methods and Applications*. Cambridge, UK: Cambridge University Press.

____. 2009. *Microeconometrics Using Stata*. College Station, TX: Stata Press.

Cincera, M. 1997. "Patents, R&D, and Technological Spillovers at the Firm Level: Some Evidence from Econometric Count for Panel Data Models." *Journal of Applied Econometrics* 12(3): 265–280.

Cox, S. 2002. "Information Technology: The Global Key to Precision Agriculture and Sustainability." *Computers and Electronics in Agriculture* 36(2/3): 93–111.

Daberkow, S.G., J. Fernandez-Cornejo, and M. Padgitt. 2002. "Precision Agriculture Adoption Continues to Grow." *Agricultural Outlook* (November), Economic Research Service, U.S. Department of Agriculture, Washington, D.C.

Daberkow, S.G., and W.D. McBride. 2000. "Adoption of Precision Agriculture Technologies by U.S. Farmers." From the proceedings of the 5th International Conference on Precision Agriculture in Minneapolis, MN, July 16–19.

____. 2003. "Farm and Operator Characteristics Affecting the Awareness and Adoption of Precision Agriculture Technologies in the U.S." *Precision Agriculture* 4(2): 163–177.

Dillman, D.A. 1978. *Mail and Telephone Surveys: The Total Design Method*. New York: John Wiley and Sons.

Feder, G., R.J. Just., and D. Zilberman. 1985. "Adoption of Agricultural Innovations in Developing Countries: A Survey." *Economic Development and Cultural Change* 33(2): 255–298.

Fountas, S., S. Blackmore, D. Ess, S. Hawkins, G. Blumhoff, J. Lowenberg-DeBoer, and C.G. Sorensen. 2005. "Farmer Experience with Precision Agriculture in Denmark and the U.S. Eastern Corn Belt." *Precision Agriculture* 6(2): 121–141.

Fountas, S., D.R. Ess, C.G. Sorensen, S.E. Hawkins, H.H. Pedersen, B.S. Blackmore, and J. Lowenberg-DeBoer. 2003. "Information Sources in Precision Agriculture in Denmark and the USA." In A. Werner and A. Jarfe, eds., *Precision Agriculture: Proceedings of the 4th European Conference on Precision Agriculture*. Berlin: Wageningen Academic Publishers.

Gibbons, G. 2000. "Turning a Farm Art into Science: An Overview of Precision Farming." Available at http://www.precisionfarming.com (accessed October 1, 2010).

Gopinath, M., and U. Vasavada. 1999. "Patents, R&D, and Market Structure in the U.S. Food Processing Industry." *Journal of Agricultural and Resource Economics* 24(1): 127–139.

Griffin, T.W., J. Lowenberg-DeBoer, D.M. Lambert, J. Peone, T. Payne, and S.G. Daberkow. 2004. "Adoption, Profitability, and Making Better Use of Precision Farming Data." Staff Paper No. 04-06, Department of Agricultural Economics, Purdue University, West Lafayette, IN.

Haab, T., and K. McConnell. 1996. "Count Data Models and the Problems of Zeros in Recreation Demand Analysis." *American Journal of Agricultural Economics* 78(1): 89–102.

Hausman, J.B., H. Hall, and Z. Griliches. 1984. "Econometric Models for Count Data with an Application to the Patents–R&D Relationship." *Econometrica* 52(4): 909–938.

Khaldi, N. 1975. "Education and Allocative Efficiency in U.S. Agriculture." *American Journal of Agricultural Economics* 57(4): 650–657.

Khanna, M. 2001. "Sequential Adoption of Site-Specific Technologies and Its Implications for Nitrogen Productivity: A Double Selectivity Model." *American Journal of Agricultural Economics* 83(1): 35–51.

Khanna, M., O.F. Epouhe, and R. Hornbaker. 1999. "Site-Specific Crop Management: Adoption of Components of a Technological Package." *Review of Agricultural Economics* 21(2): 455–472.

Larson, J.A., and R.K. Roberts. 2004. "Farmer's Perception of Spatial Yield Variability as Influenced by Precision Farming Information Gathering Technologies." Selected paper presented at the Sustainable Agriculture Education Association meetings in Tulsa, OK, February 14–18.

Larson, J.A., R.K. Roberts, B.C. English, S.L. Larkin, M.C. Marra, S.W. Martin, K.W. Paxton, and J.M. Reeves. 2008. "Factors Affecting Farmer Adoption of Remotely Sensed Imagery for Precision Management in Cotton Production." *Precision Agriculture* 9(4): 195–208.

Leathers, H.D., and M. Smale. 1991. "A Baysian Approach to Explaining Sequential Adoption of Components of a Technological Package." *American Journal of Agricultural Economics* 73(3): 734–742.

Lowenberg-DeBoer, J. 1998. "Adoption Patterns for Precision Agriculture." Technical Paper No. 982041, Society of Automotive Engineering, Warrendale, PA.

____. 1999. "Risk Management Potential of Precision Farming Technologies." *Journal of Agricultural and Applied Economics* 31(2): 275–285.

Lowenberg-DeBoer, J., and K. Erickson (eds.). 2000. *Precision Farming Profitability*. Purdue University, West Lafayette, IN.

Mishra, A.K., H. El-Osta, and J.D. Johnson. 1999. "Factors Contributing to Earnings Success of Cash Grain Farms." *Journal of Agricultural and Applied Economics* 31(3): 623–637.

Mishra, A.K., M.J. Morehart, H.S. El-Osta, J.D. Johnson, and J.W. Hopkins. 2002. "Income, Wealth, and Well-Being of Farm Operator Households." Agricultural Economics Report No. 812, Economic Research Service, U.S. Department of Agriculture, Washington, D.C.

Mishra, A.K., and T.A. Park. 2005. "An Empirical Analysis of Internet Use by U.S. Farmers." *Agricultural and Resource Economics Review* 34(2): 253–264.

Nelson, R.R., and E.S. Phelps. 1966. "Investment in Humans, Technological Diffusion, and Economic Growth." *American Economic Review* 56(2): 69–82.

Nemenyi, M., P.A. Mesterhazi, Zs. Pecze, and Zs. Stepan. 2003. "The Role of GIS and GPS in Precision Farming." *Computers and Electronics in Agriculture* 40(1/3): 45–55.

Roberts, R.K., B.C. English, J.A. Larson, R.L. Cochran, W.R. Goodman, S.L. Larkin, M.C. Marra, S.W. Martin, W.D. Shurley, and J.M. Reeves. 2004. "Adoption of Site-Specific Information and Variable-Rate Technologies in Cotton Precision Farming." *Journal of Agricultural and Applied Economics* 36(1): 143–158.

Roberts, R.K., B.C. English, and S.B. Mahajanashetti. 2000. "Evaluating the Returns to Variable Rate Nitrogen Application." *Journal of Agricultural and Applied Economics* 32(1): 133–143.

Rogers, E.M. 1995. *Diffusion of Innovations* (4th edition). New York: Free Press.

Shibusawa, S. 1998. "Precision Farming and Terra-Mechanics." Paper presented at the 5th ISTVS Asia-Pacific Regional Conference in Korea, October 20–22.

Swinton, S.M., and J. Lowenberg-DeBoer. 1998. "Evaluating the Profitability of Site-Specific Farming." *Journal of Production Agriculture* 11(4): 439–446.

Walton, J.C., D.M. Lambert, R.K. Roberts, J.A. Larson, B.C. English, S.L. Larkin, S.W. Martin, M.C. Marra, K.W. Paxton, and J.M. Reeves. 2010. "Grid Soil Sampling Adoption and Abandonment in Cotton Production." *Precision Agriculture* 11(2): 135–147.

____. 2008. "Adoption and Abandonment of Precision Soil Sampling in Cotton Production." *Journal of Agricultural and Resource Economics* 33(3): 428–448.

Whelan, B.M., A.B. McBratney, and B.C. Boydell. 1997. "The Impact of Precision Agriculture." From proceedings of the ABARE Future of Cropping in NW NSW Outlook Conference, Moore, UK, July.

Winkelmann, R., and K.F. Zimmermann. 1995. "Recent Development in Count Data Modelling: Theory and Application." *Journal of Economic Surveys* 9(1): 1–24.

Wozniak, G.D. 1989. "The Adoption of Interrelated Innovations: A Human Capital Approach." *Review of Economics and Statistics* 66(1): 70–79.

Zhang, N., M. Wang, and N. Wang. 2002. "Precision Agriculture: A Worldwide Review." *Computers and Electronics in Agriculture* 36(2/3): 113–132.