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Adoption of Precision Technologies and Perceived Improvements in Cotton Quality

Sofia Kotsiri, Roderick M. Rejesus, Michele C. Marra, and Sherry L. Larkin

This paper examines whether adoption of precision technologies, farm and farmer characteristics influence perceived improvements in cotton quality. Using data from cotton producers in twelve U.S. Southeastern states and discrete choice models, we find that the use of soil sampling, maps, participating in agricultural easement programs, farm size, university publications, and expected profitability of precision agriculture are positively associated with the probability that farmers experienced improved cotton quality. This implies that farmers should also consider the potential cotton quality benefits from these technologies, in addition to potential yield and environmental improvements, when deciding whether or not to adopt precision technologies.

Key words: cotton quality, mapping, multinomial probit, perceptions, precision technologies, soil sampling

Cotton quality is associated with seed and fiber properties that affect processing into yarn and textile products (Chee et al., 2005a). Better cotton quality is usually perceived as cleaner and whiter cotton, which is less damaged and stained from insect pests such as bollworms (Kambhampati et al., 2005). Since 95% of the value of cotton crop is in the fiber, cotton quality is what we usually refer to as fiber quality (May, 2002). The USDA has established 38 grades for cotton based on measurable attributes of its value, such as: *color* (there are 25 official color grades of American upland cotton), *leaf grade* (scale 1 through 7), *fiber length* (ranging from 23 to 31 mm), *length uniformity* (i.e., the ratio between the mean length and the upper half mean length), and *strength* (ranging from weak of 80 tppsi to very strong of 99 tppsi, where tppsi stands for total postoperative pain severity index).

The literature on precision agriculture to date has mainly focused on the effect of precision technology adoption on cotton yields rather than cotton quality, although cotton

Sofia Kotsiri is a postdoctoral assistant at Purdue University, Roderick M. Rejesus is associate professor, Michele Marra is professor, both in the Department of Agricultural and Resource Economics, North Carolina State University, and Sherry Larkin is professor in the Department of Food and Resource Economics, University of Florida. We are appreciative of the anonymous reviewer comments. Any remaining errors are the sole responsibility of the authors. The authors gratefully acknowledge partial funding by Cotton Inc., which supported this research.

quality has been listed as an important issue that needs to be addressed in precision farming research (McBratney, Whelan and Ancev, 2005). One reason for the limited studies is that automated fiber quality mapping technologies (i.e., fiber quality sensors) on cotton harvesters are not yet commercially available (Ge, Thomasson and Sui, 2012). Direct mapping of within-field variation of cotton quality characteristics is historically done by manually taking cotton samples from various locations across the field (Ge et al., 2008). This manual field sampling approach requires a great deal of time and labor; and the resulting fiber quality maps still tend to have problems matching the USDA classing office data (Calhoun et al., 1996). However, research to develop real-time fiber quality sensors is on-going (Schielack et al., 2010; Sui et al., 2008; Sui, Thomasson, and Ge, 2012) and crop quality sensing is considered a likely future trend in precision agriculture (Stewart, McBratney, and Skerritt, 2002, Stafford, 2000).

It is important to recognize that for cotton producers to achieve optimum profitability they should succeed not only in increasing crop yields but also in properly managing cotton quality (Schielack et al., 2010; Ge et al. 2011).[1] Given the role of quality premiums (and discounts) on cotton prices received by producers, Britt, Ramirez and Carpio (2002) indicate that quality considerations have important implications on the optimal profit-maximizing input levels that farmers need to apply. Hence, precision technologies that can provide information about within-field variability of fiber quality has the potential to both optimize input/management decisions and further enhance profits.

For example, a fiber quality mapping technology that can accurately identify low fiber quality versus high fiber quality areas in the field can be used to spatially vary farming inputs (such as water and fertilizer) based on both lint yield and fiber quality. Another strategy is to make use of existing fiber quality variability by segregating the crop into categories as it is harvested. Often there is a portion of the crop that is of higher quality than the rest, and its value is usually averaged with that of the rest of the crop. If the high-quality portion could be segregated, it could be sold at a higher price, while the rest of the crop could be sold at its current value. But for cotton farmers to implement either the variable rate application or segregation-harvesting strategy, the primary ingredient that is still lacking is an efficient and accurate site-specific mapping technology for measuring fiber quality in the field. Therefore, the effect of adopting this type of precision

[1] Schielack et al. (2010) attributed 80% of cotton profitability to yield and 20% to quality. Based on two cotton fields in Texas, Ge et al. (2011) indicated that fiber quality variation is about 31% as important as the yield variation in determining total cotton revenue variation, especially when interaction between yields and quality are considered. Therefore, if cotton quality is improved through adoption of precision technologies (see the proceeding discussion after this paragraph), then farm profitability has the potential to be enhanced because cotton quality determines a significant proportion of revenues (assuming the benefits from quality improvements are larger than the variable costs associated with adoption of the precision technology).

technology on cotton quality, yields, and profit cannot yet be fully evaluated because it is not widely available to cotton farmers.

Nevertheless, it is still important to examine whether adoption of existing commercially available precision farming technologies affect cotton quality. The use of existing precision technologies can still have cotton quality effects since many studies have shown that cotton quality characteristics are strongly correlated to soil properties, such as sand/clay content, pH, relative elevation, slope, and soil moisture content (Elms, Green and Johnson, 2001; Johnson et al., 2002; Ping et al., 2004). For example, Ge, Sui and Thomasson (2006b) reported that soil moisture content was strongly correlated to fiber length, strength, and length uniformity in the irrigated Texas field they studied. In another study, Ge et al. (2008) found that electrical conductivity and soil water holding capacity have strong spatial correlations with most fiber quality measures. Since spatial patterns of these different soil characteristics are already being collected through current precision technologies (e.g., specifically through site-specific information gathering technologies like soil sampling and digitized mapping), farmers could have utilized this spatial soil information to properly manage fiber quality because it is known that these properties correlate well with fiber quality attributes (Stewart, Boydell and McBratney, 2005). For example, farmers could have identified the low quality areas through electrical conductivity maps collected using current technologies, and then managed these zones to improve quality characteristics. This is evidence that information from existing precision technologies could have been used to improve fiber quality attributes in farmers' yields.

In this study, we investigate whether farmers perceive any improvements in cotton quality when they adopt currently available precision farming technologies. Other factors that may affect perceptions about cotton quality are examined as well. The significant premiums and discounts for lint quality in cotton markets necessitate a better, more quantitative understanding of the determinants of cotton quality (Britt, Ramirez and Carpio, 2002), including the effect of existing precision technologies. Producers with limited information about the quality implications of different input and technology choices are more likely to make incorrect management decisions (Ethridge and Hudson, 1998). This study makes a contribution because to the best of our knowledge it may be the first to quantitatively investigate the relationship between adoption of currently available precision technology and cotton quality (based on actual farmer survey data rather than from experimental fields). However, we use "perceived" cotton quality improvements rather than direct measures of quality due to data constraints.

Conceptual Framework

Following the study of Britt, Ramirez and Carpio (2002), we use a simple production function model that evaluates the impact of management decisions (in our case precision farming technologies) on yields and quality. We assume that cotton lint yield Y is a function of a variable input (say, fertilizer) X, and fiber quality attribute Q also depends on the same variable input X, such that:

$$\begin{aligned} Y &= f(X) \\ PR &= PR(Q) \\ Q &= f(X) \end{aligned} \tag{1}$$

where PR stands for quality premium and depends on the quality attribute. Profits Π are then defined as:

$$\Pi = (P + PR)Y - WX - FC \tag{2}$$

where P is the price per unit of yield, W the variable input price (e.g., fertilizer price) and FC the fixed cost. The first order conditions (FOC) for profit maximization are:

$$\frac{\partial \Pi}{\partial X} = P\frac{\partial Y}{\partial X} + \frac{dPR(Q)}{dX}\frac{\partial Q}{\partial X}Y + PR\frac{\partial Y}{\partial X} - W = 0 \tag{3}$$

or in terms of marginal products:

$$MP = \frac{\partial Y}{\partial X}(P + PR) + \frac{dPR(Q)}{dX}\frac{\partial Q}{\partial X}Y = W \tag{4}$$

The above conditions indicate that profits are affected by how inputs affect quality. Since inputs may affect quality, as well as quantity, the existence of quality premiums/discounts alter the amount of inputs that optimize profits. In addition, adoption of precision technologies (vs. conventional technologies) influence how these inputs affect cotton yields and quality (i.e., through the function $f(\cdot)$. Farmers who use existing precision farming technologies may be better informed about the fiber quality variability in their fields (i.e., due to the strong correlation between soil properties and fiber quality), thus they are more likely to have managed this within field quality variability properly with proper input applications, such that overall cotton quality of all fields is enhanced. Therefore, it is empirically important to determine whether farmers who adopt precision agriculture technologies perceive cotton quality improvements.

Survey and Data Description

Data for this study was collected from a survey sent to cotton producers in 12 states: Alabama (AL), Arkansas (AR), Florida (FL), Georgia (GA), Louisiana (LA), Mississippi (MS), Missouri (MO), North Carolina (NC), South Carolina (SC), Tennessee (TN), Texas (TX) and Virginia (VA). The Cotton Board in Memphis, Tennessee provided a mailing list of 13,579 potential cotton farmers for the 2007-2008 crop seasons. Following Dillman's (2000) general mail survey procedures, the questionnaire, a postage-paid return envelope, and a cover letter explaining the purpose of the survey were sent to each producer in February and March of 2009. The response rate was 12.5%.

The questionnaire asked farmers who indicated that they had adopted at least one precision farming technology whether they had experienced any improvement in cotton quality in their fields. Among the respondents of this question, 1148 in total, 159 farmers (13.8%) replied that they had observed improvements, 442 farmers (38.5%) did not perceive any improvement and 547 answered "do not know" (47.6%). On the other hand, 883 were identified as adopters of precision technologies either currently or at some point in the past.[2] This means that either some no adopters answered the question about subsequent cotton quality, or some farmers who use (or have used) the technology did not identify themselves as precision farming users in previous questions.

The farm and farmer characteristics of the survey respondents are comparable to those reported in the 2007 Census (U.S. Department of Agriculture). The number of cotton farmers surveyed, as well as farmer distribution across states, is similar to the ones reported in the 2007 Census (16,742 versus 13,579 in our survey). Mooney et al. (2010) compared the geographical distribution of the survey responses by county with the number of cotton producers reported in the 2007 Census, and found that they correspond closely. The majority of cotton farmers who answered our survey are aged 45 to 64 (59%), which is a similar proportion to the 2007 Census (55%). Farmers aged 65 and above represented only 24% of respondents in our survey, which is also consistent with the 24% found in of the 2007 Census data. In terms of acres, the proportion of farms above 500 acres in our survey was larger (58%) compared to the 2007 Census (38%). For farmers with cotton acreage below 249, we have a lower share of surveyed farms (24%) compared to the Census (42%). But the proportion of farms between 250 and 499 acres was the same for both our survey and the Census (18%). Thus, based on all these figures, we believe that our sample is representative of the population of cotton farmers (as characterized in the 2007 Census).

[2] We also included farmers who used the technology but abandoned it after several years of use, in the sense that a potential "no quality improvement" might have resulted from abandoning use of precision agriculture.

Whether the farmer reported that she/he observed improvements in cotton quality through the use of precision technologies is used as the dependent variable (*COTTON QUAL*) in this study (i.e., both in the binary probit model, as well as the multinomial probit model, discussed below). Different precision technologies adopted, along with farm and farmer characteristics, were used as explanatory variables. Regarding the explanatory variables, we believe that characteristics that affect perceptions about improvements in environmental quality would also impact perceptions about cotton quality improvements. Thus we followed the work of Larkin et al. (2005), as well as Larson and Roberts (2004), who explored how the use of precision technologies influences perceived yield variability. Farm characteristics such as total acreage, average yields, farm location and participation in agricultural easement programs were assumed to be important determinants of perceived improvement in cotton quality. These farm characteristic variables are described in more detail as follows: (1) The total acreage (*FARM SIZE*) is the sum of rented and owned acres for dry-land (and when it is not available, we used the total acreage of irrigated land) for the 2007 crop season. We would expect a positive sign for farm size, in the sense that the more the acres the higher the possibility of observing cotton quality improvement as compared to a small farm. (2) Similarly, higher average cotton lint yields (*YIELDS*) may indicate greater probability of observing cotton quality improvement, since the yields also reflect land quality. (3) Location was captured by 11 dummies (i.e., *AL, AR, FL, GA, LA, MS, MO, NC, SC, TN, VA*) that tested whether farmers in these states had higher or lower probabilities to observe cotton quality improvement relative to farmers in Texas, which is used as the benchmark state due to its high number of farmers. The signs of the states variables cannot be hypothesized a priori. (4) Easement programs are legal agreements designed to protect agricultural land by restricting the development of its residential or commercial use (Schear and Blaine, 1998). If a farmer has participated in an agricultural easement program (either voluntarily or received some payment), she/he will probably care for cotton quality more, thus *AG EASEMENT* is expected to have a positive influence on the probability of experiencing improvements in cotton quality.

Several farmer characteristics were hypothesized to affect the probability that a farmer would perceive cotton quality improvements. These farmer characteristics are discussed as follows: (1) More educated (*EDUC*) farmers will more likely possess the knowledge on quality requirements, fiber properties and production practices that improve cotton quality. (2) Similarly, farmers who use a computer in their farm management (*COMPUTER*) are typically more innovative and eager to improve their practices, thus more likely to attribute any potential improvements in quality following the use of technology. (3)-(4) Younger farmers (*AGE*) have, in general, longer planning horizons (*PLAN*), thus we would expect that they are more likely to perceive improvements in cotton quality, implying negative sign for *AGE* and positive sign for

PLAN. However, younger farmers may have also less experience in farming, so there is a small probability that they have observed quality benefits. Therefore, the sign of *AGE* cannot be hypothesized in advance. (5) On the contrary, producers with more experience in farming (*EXPERIENCE*) may have more likely experienced improvements in cotton quality over the years through the use of precision technologies. University sources, such as Extension or publications, provide information about the precision agriculture and its benefits on environment, quality and yields. (6) Therefore, we would expect a positive impact of *PUBLICATION* on perceptions about cotton quality improvement. (7) Studies have shown that organic material may improve soil fertility (MacDonald, , et al., 2009) and especially the use of manure, which is a great source of nitrogen, phosphorus, and potassium, can yield higher soil benefits than inorganic fertilizers (Risse, et al., 2006). Vories, Glover, and Bryant (1999) found that poultry litter can significantly reduce the total runoff and sediment losses in cotton fields relatively to commercial fertilizers. Hence, we would expect manure application (*MANURE*) to positively affect the perceptions about increased cotton quality. (8) Farmers whose income comes mainly from farming (*FARM INCOME*) would more likely invest in strategies that improve cotton quality, so they would more likely indicate cotton quality improvements from the subsequent use of precision technologies. (9-10) The literature on precision agriculture has showed that farmers who foresee that precision technologies will be important in the future (*EXP IMPORTA*) and those who expect that precision agriculture will be profitable in five years from the time of the survey (*EXP PROFIT*) had higher probabilities of adoption (Banerjee et al., 2008, Torbet et al., 2007, Roberts et al., 2004). Larkin et al. (2005) found that these expectations about future profit and importance indicate higher probability of reporting environmental quality improvements through the use of PF. We use the (11) perceived improvement in environmental benefits (*ENVIRON_BEN*) as an independent variable in our estimation as well. Quality and environmental benefits can be interrelated in the eyes of producers, thus, we would expect a positive impact of these variable on perceived cotton quality improvement.

In this study, we can distinguish between the following types of precision technologies: the site specific information gathering technologies (SSIG) and the variable rate input application (VRT). The first group, can be divided into: (1) yield monitors with and/or without GPS denoted as *MONITORS*, (2) grid and/or zone soil sampling denoted as *SAMPLING*, (3) aerial photos and/or satellite images denoted as *SATELLITE*, (4) soil survey maps, *COTMAN* plant mapping and/or digitized mapping denoted as *MAPS*, and (5) *OTHER* includes the less used technologies such as Handheld GPS/PDA and/or Electrical conductivity. The role of existing site specific information gathering technologies is to identify variation in physical and chemical properties of the field and give farmers the opportunity to apply their inputs based on location-specific needs. Given the strong correlation between soil properties and fiber quality, we would expect that, in general, the use of SSIG technologies would increase the probability that a producer would observe improvement in cotton quality, relative to those who did not adopt the technology. However, which types of SSIG technologies indicate higher or lower probability of perceived improvement in cotton quality cannot be determined a priori. Regarding the second group, we consider variable rate application of the following inputs: drainage, fertility or lime, seeding, growth regulator, harvest aids, fungicide, herbicide, insecticide, and irrigation. Potassium and K-fertilizer applications improve significantly the fiber quality mostly in terms of length uniformity and strength (Oosterhuis et al., 1990). However, the very small number of responses does not allow the use of the VRT observations for the nine inputs as nine explanatory variables, and thus we had to restrict our analysis only to the impact of SSIG technologies on perceived cotton quality improvement. The descriptions of the variables used in the study are summarized in Table 1.

Empirical Approach

Binary Probit Model

Actual cotton quality improvements are a function of observed characteristics X_i (such as adoption of SSIG technologies and demographics) and unobserved characteristics ε_i. Assuming a linear additive relationship (Verbeek, 2008), we can specify a quality equation as $Y_i^* = X_i'\beta + \varepsilon_i$, where ε_i are normally distributed and homoskedastic $\varepsilon_i \sim N(0,1)$. However, actual cotton quality is an unobservable variable in our case (i.e., Y_i^* is a latent variable). Given this, the surveyed farmers report perceived improvements in cotton quality if the latent variable Y_i^* exceeds a certain threshold level, which can be set to zero. Consequently, $Y_i = 1$ ($Y_i^* > 0$) if the farmer experienced improvement in cotton quality through the use of PF technologies, or $Y_i = 0$ ($Y_i^* \leq 0$) if the farmer either did not experience any improvement in cotton quality through the use of PF technologies or did not know whether he did. The binary variable (Y_i) is observable in our data such that a binary probit regression model can be estimated (i.e., $Y_i = X_i'\beta + \varepsilon_i$,).

Table 1: Description of dependent and independent variables

Variables	Description
Dependent Variable	
COTTON QUAL	(*Probit*) Farmer experienced improvement in cotton quality (yes=1; no or don't know=0)
	(*MNL/MNP*) Farmer experienced improvement in cotton quality (yes=1; no=0 and don't know=2)
Independent Variables	
MONITORS	Farmer used yield monitors (with or w/o GPS) to access the yield variability (yes=1, no=0)
SAMPLING	Farmer used soil sampling (grid or zone) to access the yield variability (yes=1; no=0)
SATELLITE	Farmer used aerial photos or satellite images to access the yield variability (yes=1; no=0)
MAPS	Farmer used maps (soil survey maps, COTMAN plant mapping or digitized mapping) to access the yield variability (yes=1; no=0)
OTHER	Farmer used other technologies (handheld GPS/PDA or electrical conductivity) to access the yield variability (yes=1; no=0)
FARM SIZE	Total acreage of dry land (sum of rented and owned acres) for the 2007 crop season
YIELDS	Estimate of average cotton lint yield per acre for 2007 crop season
EDUC	Years of Formal Education Excluding Kindergarten
AGE	Age of the farm operator (as of the 2009 survey year)
EXPERIENCE	Number of Years farming
EXP_IMPORTA	Farmer perceived that precision farming would be important in five years from now (yes=1; no=0)
EXP_PROFIT	Farmer perceived that precision farming would be profitable to use in the future (yes=1; no=0)
FARM_INCOME	Percentage (%) of 2007 taxable household income coming only from farming sources
COMPUTER	Farmer uses computer for farm management (yes=1, no=0)
MANURE	Farmer applied manure on his/her fields (yes=1; no=0)
PUBLICATION	Farmer used University publications to obtain precision farming information (yes=1; no=0)
PLAN	Years to plan farming in the future
AG_EASEMENT	The farm currently has agricultural easement (yes=1, no or don't know=0)
ENVIRON_BEN	The perceived improvements in environmental quality through the use of precision farming (yes=1, no or don't know=0)
	Dummies for Farm Location
AL	Farm located in Alabama (yes=1, no=0)
AR	Farm located in Arkansas (yes=1, no=0)
FL	Farm located in Florida (yes=1; no=0)
GA	Farm located in Georgia (yes=1; no=0)
LA	Farm located in Louisiana (yes=1, no=0)
MS	Farm located in Mississippi (yes=1; no=0)
MO	Farm located in Missouri (yes=1; no=0)
NC	Farm located in North Carolina (yes=1; no=0)
SC	Farm located in South Carolina (yes=1; no=0)
TN	Farm located in Tennessee (yes=1, no=0)
TX	Farm located in Texas (yes=1, no=0)
VA	Farm located in Virginia (yes=1; no=0)

OTHER was dropped during estimation to avoid the dummy variable trap

The probability that the individual i perceives $Y_i = 1$ can be derived from the latent variable and the decision rule, i.e.,

$$P\{Y_i = 1 \mid X_i\} = P\{Y_i^* > 0 \mid X_i\} = P\{X_i\beta + \varepsilon_i > 0 \mid X_i\} = P\{\varepsilon_i > X_i\beta \mid X_i\} = 1 - F(-X_i\beta) = F(X_i\beta) \quad (5)$$

where F denotes the distribution function of ε_i (the standard normal in our case). The likelihood function is given by:

$$LogL(\beta) = \sum_{i=1}^{N} Y_i \log F(X_i'\beta) + \sum_{i=1}^{N}(1-Y_i)\log(1-F(X_i'\beta)), \quad (6)$$

and the coefficients are estimated with maximum likelihood.

Contrary to the linear regression model, the parameters (βs) cannot be directly interpreted as the marginal effects on the dependent variable Y_i. Thus, for the binary probit model, the marginal effects are defined as:

$$\frac{\partial E(Y_i|X_i)}{\partial X_{i,k}} = \frac{\partial P(Y_i=1|X_i)}{\partial X_{i,k}} = F(X_i^{'}\beta)\beta_k \tag{7}$$

The binary probit empirical model is then specified as follows:

$$\begin{aligned} COTTON\_QUAL_i = {} & \beta_0+\beta_1 MONITORS+\beta_2 SAMPLING+\beta_3 SATELLITE \\ & +\beta_4 MAPS+\beta_5 FARM\_SIZE+\beta_6 YIELDS+\beta_7 EDUC \\ & +\beta_8 AGE+\beta_9 EXPERIENCE+\beta_{10} EXP\_IMPORTA \\ & +\beta_{11} EXP\_PROFIT+\beta_{12} FARM\_INCOME \\ & +\beta_{13} COMPUTER+\beta_{14} MANURE+\beta_{15} PUBLICATION \\ & +\beta_{16} PLAN+\beta_{17} AG\_EASEMENT+\beta_{18} ENVIRON\_BEN \\ & +\beta_{19} LOCATION\ DUMMIES+\varepsilon_i \end{aligned} \tag{8}$$

Multinomial Probit Model

To evaluate whether the substantial number of the "do not know" answers (n=547) has an impact on the probability of perceived cotton quality improvement, we also estimated a Multinomial Probit Model (MNP). For an individual i we assume a random utility model $Y_{ij} = X_i'\beta_j + u_{ij}$ associated with the following alternatives: j=0, if the farmer did not experience any improvements in cotton quality after the use of precision technologies, j=1 if she/he perceived improvements in cotton quality and j=2 if she/he "did not know" whether there was an improvement. Again, X_i' reflects the set of observed characteristics, β the vector of parameters to be estimated and u_{ij} the stochastic error term. In the MNP model the error follows a multivariate normal distribution with covariance matrix Σ where Σ is not restricted to be diagonal matrix.

Assuming that the disturbances of the different combinations are correlated across choices (Greene 1997):

$$\begin{aligned} & u \sim MND(0,\Omega) \\ & \Omega = \mathrm{I}_N \otimes \Sigma \\ & \Sigma = \mathrm{E}(u_i u_i^{'}) \end{aligned} \tag{9}$$

Thus the probability to choose category j can be written as:

$$
\begin{aligned}
(10) \qquad P(Y_i = j \mid X_i) &= P(Y_{ij}^* > Y_{i1}^*, \ldots, > Y_{i(j-1)}^*, Y_{ji}^* > Y_{i(j+1)}^*, \ldots, Y_{ij}^* > Y_{iM}^*) \\
&= P((u_{ij} - u_{i1}) > X_i'(\beta_1 - \beta_j), \ldots, (u_{ij} - u_{i(j-1)}) > X_i'(\beta_{(j-1)} - \beta_j), \\
&(u_{ij} - u_{i(j+1)}) > X_i'(\beta_{(j+1)} - \beta_j), \ldots, (u_{ij} - u_{iM}) > X_i'(\beta_M - \beta_j))
\end{aligned}
$$

which holds for every subset of eligible combinations including M and j. To ensure identification, β_j is set to zero for one of the categories, and coefficients are then interpreted with respect to that category, called the base category (Cameron and Trivedi, 2009). The maximum likelihood procedure is again applied to estimate the model.

Results and Discussion

The estimated parameters of the binary probit model along with the average marginal effects, their delta standard errors and p-values are presented in Table 3.[3]

The likelihood ratio test was 173.68 and statistically significant at the 99% level, indicating an overall good fit of the model. Furthermore the Wald chi-squared test shows that the coefficients of the MNP model are all statistically different from zero, when considered jointly. Multicollinearity diagnostics (Ender, 2003) indicated a mean VIF (Variance Inflation Factor) of 1.37 and Tolerance levels between 0.74 and 0.94. The only correlation coefficients that did not follow the condition indices were *AGE* and *EXPERIENCE*, both of which were not statistically significant.

Only the statistically significant average marginal effects (AME) are interpreted here and they all had the hypothesized signs. A marginal effect is calculated for each observation, and then each computed effect is averaged.[4] Use of soil sampling, maps, participating in agricultural easement, total acres planted, expected future profitability of precision technologies and perceived improvements in environmental quality, all positively affected the probability that a farmer perceived improved cotton quality after the adoption of SSIG technologies. A 10 fold increase in *SAMPLING* increases the probability of perceived cotton quality improvement by 0.59, whereas a 10 fold increase in *MAPS* increases the probability of perceived cotton quality improvement by 0.72. The effect of the other two SSIG technologies (*MONITORS* and *SATELLITE*) is also positive but not statistically significant. These results are consistent with the fact that soil sampling along with mapping technologies have been used for a longer period of time compared to yield monitors and satellite technologies. Soil sampling, in particular, has the lower

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[3] Estimates of location dummies are not statistically significant and are not presented in the tables, but are available upon request.

[4] The multinomial probit coefficients are interpreted based on comparison with the base category, which is "Yes, I have perceived improvements in cotton quality following the use of precision technologies."

Table 2: Summary Statistics

Variables	Mean	St. Dev.	Min	Max
Dependent Variable				
COTTON QUAL	0.138	0.345	0	1
	1.091	0.924	0	2
Independent Variables				
MONITORS	0.058	0.234	0	1
SAMPLING	0.194	0.395	0	1
SATELLITE	0.047	0.213	0	1
MAPS	0.056	0.231	0	1
OTHER	0.033	0.18	0	1
FARM SIZE	854.78	1012.98	5	18425
YIELDS	1134.43	628.91	1	3600
EDUC	14.16	2.521	0	25
AGE	56.09	12.699	23	95
EXPERIENCE	31.637	13.521	0	79
EXP_IMPORTA	0.697	0.36	0	1
EXP_PROFIT	0.534	0.498	0	1
FARM_INCOME	72.248	29.453	0	100
COMPUTER	0.537	0.498	0	1
MANURE	0.181	0.385	0	1
PUBLICATION	0.348	0.476	0	1
PLAN	3.749	1.553	1	5
AG_EASEMENT	0.085	0.279	0	1
ENVIRON_BEN	0.264	0.441	0	1
Location Dummies				
AL	0.063	0.244	0	1
AR	0.041	0.199	0	1
FL	0.016	0.126	0	1
GA	0.099	0.299	0	1
LA	0.044	0.206	0	1
MS	0.072	0.259	0	1
MO	0.022	0.149	0	1
NC	0.095	0.294	0	1
SC	0.03	0.172	0	1
TN	0.056	0.23	0	1
TX	0.445	0.497	0	1
VA	0.011	0.107	0	1

Table 3: Maximum Likelihood Estimates and Average Marginal Effects (AME) of the Probit Model (N=783)

Variable	Estimate	St.E	P-Value	AME	St.E	P-Value
CONSTANT	-1.619 **	0.706	0.022	N/A	N/A	N/A
MONITORS	0.102	0.220	0.643	0.015	0.033	0.643
SAMPLING	0.388 **	0.159	0.015	0.059 **	0.024	0.015
SATELLITE	0.108	0.234	0.645	0.016	0.035	0.645
MAPS	0.472 **	0.216	0.029	0.072 **	0.032	0.028
FARM SIZE	0.0001 *	0.00007	0.080	0.00002 *	0.00001	0.079
YIELDS	0.00009	0.0001	0.450	0.00001	0.00001	0.449
PUBLICATION	0.17	0.153	0.265	0.026	0.023	0.265
COMPUTER	-0.156	0.165	0.343	-0.023	0.025	0.343
EXP_IMPORTA	-0.218	0.308	0.479	-0.033	0.047	0.479
EXP_PROFIT	0.441 **	0.199	0.027	0.067 **	0.03	0.027
FARM_INCOME	-0.0003	0.002	0.894	-0.00005	0.0004	0.894
AG_EASEMENT	0.385 *	0.212	0.070	0.058 *	0.032	0.069
PLAN	-0.011	0.047	0.816	-0.001	0.007	0.816
MANURE	0.086	0.169	0.608	0.013	0.025	0.608
EXPERIENCE	0.002	0.011	0.808	0.0004	0.001	0.808
ENVIRON_BEN	1.357 ***	0.151	0.000	0.207 ***	0.02	0.000
AGE	0.003	0.011	0.750	0.0005	0.001	0.750
EDUC	-0.048	0.029	0.101	-0.007	0.004	0.100
Prob >chi2 = 0.0000						
Pseudo R^2=0.2831						
LR chi2 (28) = 173.68						

Notes: Single, double, and triple asterisks (*,**,***) denote that $p< 0.10$, $p<0.05$ and $p<0.01$, respectively

abandonment rate with only 0.05% rate of discontinuing its technology use. Hence, cotton producers have possibly sufficient time to evaluate its costs and benefits (Walton et al., 2008), which in turn may also have allowed them to see its potential effects on quality. In addition, sampling and digital mapping technologies give information about within-field variability of soil properties that are correlated with fiber quality. It is possible that producers who adopted sampling and digitized mapping techniques are the ones who took advantage of the quality information implied from these technologies, and consequently optimized input/management decisions to improve overall fiber quality for their fields. Hence, these producers are the ones that recognize cotton quality improvements.

Farmers who have received payment to use and develop the land for agricultural purposes only, will more likely care more about cotton quality than profits. Therefore a 10-fold increase in the probability of participating in agricultural easement programs will more likely increase the perceived quality improvement by 0.59. Operators of larger farmers are more likely to be well informed about the benefits of precision technologies thus more likely to observe improvements in cotton quality. Regarding the positive coefficient of environmental perceptions, farmers have experience in weather and soil conditions that affect environmental and cotton quality. Hence, improved environmental conditions will more possible imply improved cotton quality.

The performed multinomial probit (MNP) relaxes the Independence of Irrelevant Alternatives Assumption (IIA). The IIA assumption implies that adding or deleting alternative outcome categories does not affect the odds among the remaining outcomes. The binary probit estimates are robust with both the MNP regression estimates, presented in Table 4.

Table 4: Estimates of Average Marginal Effects (AME) of the Multinomial Probit Model (N=783)

	Y=0; No			Y=2; Don't Know			Y=1; Yes		
Variable	AME	St. E	P-Value	AME	St. E	P-Value	AME	St. E	P-Value
MONITORS	-0.005	0.069	0.933	-0.011	0.070	0.871	0.017	0.033	0.609
SAMPLING	0.023	0.041	0.575	-0.082 *	0.042	0.052	0.059 **	0.024	0.015
SATELLITE	-0.029	0.070	0.678	0.013	0.072	0.857	0.016	0.035	0.655
MAPS	-0.039	0.067	0.558	-0.031	0.068	0.640	0.071 **	0.032	0.030
FARM SIZE	4.79E-06	0.000	0.834	-0.00002	0.00002	0.277	0.00002 *	0.00001	0.087
YIELDS	-0.00005 *	0.00003	0.054	0.00004	0.00003	0.156	0.00001	0.00001	0.448
PUBLICATION	-0.1 **	0.037	0.007	0.074 *	0.038	0.055	0.026	0.023	0.260
COMPUTER	-0.026	0.038	0.500	0.05	0.040	0.210	-0.024	0.025	0.330
EXP_IMPORTA	-0.121 **	0.058	0.039	0.159 **	0.063	0.012	-0.038	0.046	0.416
EXP_PROFIT	-0.074 *	0.040	0.068	0.008	0.043	0.847	0.066 **	0.030	0.028
FARM_INCOME	0.0009	0.0006	0.129	-0.0009	0.0006	0.161	-0.00004	0.0004	0.924
AG_EASEMENT	-0.059	0.062	0.341	-0.001	0.062	0.986	0.06 *	0.032	0.064
PLAN	0.008	0.011	0.442	-0.006	0.011	0.565	-0.001	0.007	0.789
MANURE	0.006	0.043	0.885	-0.019	0.044	0.657	0.013	0.025	0.598
EXPERIENCE	-0.002	0.002	0.249	0.002	0.002	0.346	0.0003	0.001	0.813
ENVIRON_BEN	-0.068	0.045	0.135	-0.138 ***	0.046	0.003	0.206 ***	0.020	0.000
AGE	0.002	0.002	0.266	-0.003	0.002	0.200	0.0005	0.001	0.744
EDUC	0.015 **	0.007	0.032	-0.008	0.007	0.268	-0.007	0.004	0.106
Prob >chi2 = 0.0000									
Wald chi2 (58) = 188.20									

Notes: Single, double, and triple asterisks (*,**,***) denote that p< 0.10, p<0.05 and p<0.01, respectively

As far as those who did not perceive cotton quality benefits, farmers who did not obtain information about PF from University publications (*PUBLICATION*), have lower yields (*YIELDS*) do not expect that PF will be important (*EXP_IMPORTA*) or profitable

(*EXP_PROFIT*) in the near future, and had a higher educational attainment (*EDUC*) will more likely report that they did not observe cotton quality benefits from the PF use. Farmers, who do not read University publications (*PUBLICATION*) may not understand the site-specific management practices that can possibly improve cotton quality in the production system, thus are less likely to experience cotton quality improvements. Likewise, lower average yields (*YIELDS*) are related to either lower or unimproved quality outcomes. The impact of perceptions regarding the future of precision technologies (in our case profitability and importance of precision agriculture) is important because farmers could make predictions based on the experience they have obtained from cotton farming. Therefore producers, who do not believe that PF will be important or profitable, will more likely not observe improvements in crop quality. Last, with respect to educational level, farmers with more years in formal education will more likely make decisions based on profit criteria (Kotsiri et al., 2013). Hence more educated farmers will more likely value yields than quality so they will less likely observe improvements in cotton quality following precision farming adoption.

Conclusions

This paper examines whether adoption of precision technologies and other production factors influence perceived improvements in cotton quality. Global positioning systems (GPS), geographical information systems (GIS), computers and management practices are technologies that influence cotton quality. Hence, understanding how precision farming technologies affect cotton quality may be important in helping guide optimal profit-maximizing management decisions in the future.

Using data from farmers in the Southeastern United States and through discrete choice models, we find that use of soil sampling, mapping technologies, participating in agricultural easement, total acres planted, university publications, and expected future profitability of precision technologies all positively affected the probability that a farmer perceived improvements in cotton quality. Most previous studies focus on the yield improvements and environmental benefits from precision farming (i.e., water quality), but our results suggest that the adoption of precision farming technologies may also benefit farmers in terms of increased cotton quality. This is important information for farmers contemplating adoption or continued use of this technology because it shows another potential benefit for utilizing precision technologies in their farms.

Results of our study provide an important insight that could be of use to researchers, technology manufacturers, and dealers. Since our results suggest that precision farming can potentially influence cotton quality, researchers can build on this insight and collect data on more objective measures of quality to further discern whether existing precision technologies have effects on actual quality attributes, like fiber length and strength. More comprehensive economic models akin to the study of Britt, Ramirez, and Carpio (2002) can be developed to further understand how precision agriculture technologies change optimal input use that maximizes profits. The precision technology impacts on quality should also lead manufacturers and dealers to further develop and improve precision farming tools that can directly sense cotton quality and improve production efficiency (as discussed in the introductory section). Extension educators may also utilize information in this study to further inform their constituents about the potential cotton quality improvements from precision technology use. Hence, precision technologies that will directly encompass both lint yields and cotton quality may be the important next step to further improve cotton production efficiency in the future.

A challenge would be to further develop and improve precision technologies and their sensor systems in order to integrate multiple crop data and provide more detailed information about cotton lint yields, fiber quality and their interactions. This would allow researchers to have more data needed for further analysis of the relationship between precision technologies and quality. Another challenge is the enhancement of the data quality algorithms and the communication of the data quality to the end users. This stage is very critical because errors in the data could cause wrong managerial decisions that would lead to inefficient resource use and environmental risks (Thessler et al., 2011). Lastly, issues of applications compatibility and maintenance need also to be taken into consideration in the future.

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