Adoption and Extent of Adoption of Georeferenced Grid Soil Sampling Technology by Cotton Producers in the Southern US

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Abstract

This study investigates the producer/farm characteristics that influence the adoption and extent of adoption of georeferenced grid soil sampling technology, using the two-part model, among cotton producers in the southern US. The extent of adoption is defined as the number of acres managed with the technology. Soil sampling is seen as the foundation of precision agriculture. The study uses a 2013 survey data on active cotton producers in 14 southern US states conducted by Cotton Incorporated. The study identified producers' awareness of a cost-share reimbursement program, percentage of income from cotton production, the use of yield map, ownership of livestock, land acreage devoted to other crops, and cotton productions in Mississippi and Tennessee as important variables that influence the adoption and the extent of adoption of georeferenced soil sampling technology.

***Keywords**:* Precision Agriculture, Soil Sampling, Two-part Model, Cotton.

JEL codes: Q55, D22

1. Introduction

Precision agriculture can potentially help producers to use agricultural inputs efficiently and also improve the environment (Fountas et al. 2006, Cowan, 2000, Robert et al. 2000 and Whelan and McBratney, 2000). This agricultural practice uses site-specific technologies, such as geo-referenced soil sampling technologies, global positioning systems, geographic information systems and others to gather information about the variability of yield and/or soil characteristics at different locations in a field to manage inputs (Robert et al. 2000). Yield variability is the most important within field characteristic that influences the adoption of precision agriculture technologies (Kenneth et al. 2010, Zhang et al. 2002).

The yield of a crop is largely influenced by the availability and distribution of soil nutrients in a field (Zhang et al. 2002). Therefore, effective soil nutrient management will depend on the ability of the producer to capture the distribution of soil nutrients. The distribution of soil nutrients is mostly captured with soil sampling technologies, which is stored in a soil test map (Wollenhaupt and Wolkowski, 1994). The soil test map has been the main technology used in making prescription maps, upon which variable rate application of agricultural inputs are based (Fleming and Westfall, 2000, and Franzen and Peck, 1995). Among others, a typical soil test will include the determination of available phosphorus (P), exchangeable potassium (K), calcium (Ca), and magnesium (Mg), their saturation percentages, the cation exchange capacity (CEC), pH, and lime requirement (Adamchuk, 2004).

Georeferenced grid soil sampling and zone management soil sampling are the two main soil sampling technologies currently used by producers (Flowers et al. 2005). These soil sampling technologies, by capturing the distribution of soil nutrients within a field, form the foundation of precision agriculture practice, in particular, variable input applications. However, the literature on producers' adoption behavior of these soil sampling technologies is scanty. Lambert et al. (2014), modeled simultaneously the adoption of georeferenced precision soil sampling technology and the time interval until soil retesting (the extent of adoption), using a Logit model and a Poisson hurdle model, respectively. This study will complement the study of Lambert et al. (2014) by identifying the producer/farm characteristics that can affect the adoption and extent of adoption of

georeferenced grid soil sampling technology contemporaneously. That will be the objective of the study. The extent of adoption in this study is defined as the land acreage that is managed with the technology; whiles the extent of adoption in Lambert et al. (2014) is defined as the time interval until the soil is retested. Georeferenced soil sampling technology is like a traditional soil sampling technology, but modified with some precision agriculture tools like global positioning systems (GPS). This study focuses on georeferenced grid soil sampling technology because it has been shown that it is the most effective method of soil sampling (Koch et al. 2004). It is also profitable for higher-value and/or higher yielding crops such as cotton, because of the relatively higher cost associated with the technology compared to its alternatives (Lowenberg-DeBoer, 1998). The results of this study could help extension, precision agriculture agribusinesses and other stakeholders design appropriate outreach programs to promote georeferenced soil sampling technology adoption, and as such promote precision agriculture. It could also help the Federal and State Governments design appropriate policy instruments to promote the adoption of georeferenced soil sampling technologies in particular, and precision agriculture adoption in general.

The study is structured into six sections. In section 2, a literature review of the relevant studies on georeferenced soil sampling technologies is provided. Economic theory is used to explain the reason why georeferenced soil sampling technologies (precision agriculture technologies) will be adopted by cotton producers, given the status quo practice, in section 3. In section 4, the econometric models proposed to achieve the objectives of this study are discussed. The results of the study are discussed in section 5. The closing section, section 6, includes the conclusion of the study.

2. Literature Review

The two main soil sampling technologies used by producers in the US are the grid and zone management soil sampling technologies (Flowers et al. 2005). Given that the spatial distribution of soil attributes is complex, the precision of soil sampling usually increases as the use of grid soil sampling technology is intensified, with regards to smaller grid sizes and a number of grids used (Gotway et al. 1996, Wollenhaupt and Wolkowski, 1994). Koch et al. (2004) estimate the average cost of grid soil sampling to be about $24.7

per hectare. Typical costs associated with grid soil sampling are labor costs, sample analysis costs, and generation of a digital application map (Koch et al. 2004). Even though grid soil sampling is the most effective way of soil sampling, it is limited by the uncertainty concerning the optimal grid size to use and the high cost associated with its use (Koch et al. 2004 and Fleming and Westfall, 2000).

Zone management soil sampling is an alternative to grid soil sampling. This method uses spatial information to define management zones, from which soils are sampled. Doerge (1999), defines management zone as a sub-region of a field that is uniform in yield limiting factors, like pest infestation, nutrient profile and so on, for which a single rate of a specific crop input is appropriate. Soil map information, topography, remote sensing readings, soil electrical conductivity readings, producer experiences, and yield map information are often used to classify management zones are (Flowers et al. 2005). For instance, in terms of topography, it is known that increased crop yields at downslope positions are attributable to the deposition of soil, organic matter, and nutrients from upslope positions and additional plant available water (Fleming and Westfall, 2000). Comparatively, yield maps offer many advantages as a tool to define management zones in the US (Flowers et al. 2005). This is because yield information is routinely collected by producers in the US (Flowers et al. 2005). Among others, typical costs associated with zone management soil sample are the cost of aerial imagery, farmer and agronomist consultations of topography and past management experiences, and generation of digital application maps (Koch et al. 2004). The cost of yield monitoring systems is included as part of the cost precision agriculture equipment since they are now integrated into most of the technologies used in precision agriculture (Koch et al. 2004). Fleming and Westfall (2000) have shown that zone management soil sampling compared favorably with grid soil sampling in the development of variable rate application maps for application of nitrogen. They recommended that zone management soil sampling is a viable alternative since it is relatively less expensive to implement (Fleming and Westfall, 2000).

3. Conceptual Model

This study assumes that cotton producers will seek to maximize the expected utility of the present value of net farm profits, obtained within a single farming season and in multiple seasons (N seasons). For each season a producer uses a given technology (either precision agriculture or uniform input application) to combine inputs (in this study assumed to be only capital and labor) to produce cotton, expressed in bales per acre. In this study, precision agriculture technology considered is georeferenced grid soil sampling technology.

The production function of cotton is assumed to be well behaved and has the following properties (Mas-Collel et al. 1995): a) cotton output is non-decreasing in inputs; b) the marginal products of capital and labor are positive; c) the law of diminishing returns of inputs holds; and d) no free lunch, that is, if no capital and labor are used, cotton output will be zero, and as such zero farm profits (negative, if fixed costs are considered) will result. Further, it is assumed that the producer's attitude towards production risk is captured by a von Neumann-Morgenstern type utility function.

Therefore, following Sandmo (1971) and Feder (1977), the problem of a risk averse cotton producer will be to maximize the expected utility associated with the difference between the present values of total revenue and total cost associated with cotton production. This is expressed mathematically as:

$$(1)\quad \max_{x_{ki}} E\big(U(\pi)\big) = E\left(U\left(\sum_{i=1}^{N}\left(\frac{p_{ci}\,(1-\sigma)f(x_{ki};y_i)}{(1+r)^{i-1}} - \frac{(FC+C(x_{ki}))}{(1+r)^{i-1}}\right)\right)\right)$$

where:

E: the expectation operator; U: the utility operator; $f(x_{ki};y_i)$: production function technology; y_i is cotton output in season i in bales/acre; σ: yield variability; $C(x_{ki})$: total variable cost ($C(x_{ki}) = w_{ki}.x_{ki}$, where w_{ki} is the price of the kth input in season i and x_{ki} is the kth input in season i); FC : total fixed cost; P_{ci}: Price of cotton in season i; r : Market interest rate; N: the number of seasons.

Assuming an interior solution, the first order condition for optimization is:

$$(2)\quad E\left(U' * \left(\frac{p_{ci}\,(1-\sigma)f'(x_{ki};y_i)}{(1+r)^{i-1}} - \frac{C'(x_{ki})}{(1+r)^{i-1}}\right)\right) = 0$$

The variables $f'(x_{ki};y_i)$ and $C'(x_{ki})$ are the marginal product and marginal cost, respectively, associated with the kth input in season i. The second order condition for the maximization problem is that the corresponding Hessian matrix should be negative definite. This condition assumes that marginal utility should be positive, and the first derivate of marginal utility be negative (Feder, 1977). Subsequently, a risk averse behavior is assumed for this maximization problem (Feder, 1977).

From first order conditions, the optimal input demand and cotton output can be derived. Subsequently, the derived profit can be obtained. The expected utility associated with derived profit is given as:

$$(3)\ E(U(\pi^*(p_c,\sigma,r,w_k) = E\left(U\left(\sum_{i=1}^{N}\frac{(p_c(1-\sigma)f(x^*{}_{ki};y^*{}_i)}{(1+r)^{i-1}} - \frac{(FC+C(x^*{}_{ki}))}{(1+r)^{i-1}}\right)\right)$$

$$(4)\ \frac{\partial(E(U(\pi^*))}{\partial\sigma} < 0$$

From equation (3), the expected utility of farm profits associated with precision agriculture will be higher than that for uniform input management (status quo). This is because, given a certain level of cotton output, precision agriculture will result in the more efficient use of inputs, as compared to a uniform input management. Importantly, this efficiency gain in input use must be strictly more than the change in fixed cost associated with precision agriculture. Therefore, a producer's expectations of the future profitability of precision agriculture will influence the adoption or otherwise of the technology. Also, it is expected that the higher the yield variability (field/spatial attribute variability), the lower will be the producer's expected utility. The producer would be expected to adopt precision agriculture since it can be used to lower yield variability, all other things being equal.

4. Empirical Model

The present study assumes that producers' decisions to adopt a soil sampling technology (participation equation) and also the extent of adoption (intensity equation) follow two different but related stochastic processes. These two decisions of the cotton producer will be explained with the Heckman two-stage model (proposed). At the first stage of the two-stage decision process, the cotton producer contemplates on whether to adopt the technology or not. The producer will adopt the georeferenced soil sampling technology if the expected utility from its adoption (U_1) is greater than that from non-adoption (U_0). The difference between the expected utilities ($U^* = E(U_1) - E(\ U_1)$) is called a latent decision variable, which is unobservable to the researcher. According to the random utility model, the utilities associated with a given technology is decomposed into the systematic and stochastic components (Cameron and Trivedi, 2005). Given that the latent variable is positive, the probability that the cotton producer will adopt the technology is given as equation 5 below:

(5) $Prob(d_i \ = 1|x) = \Pr\ (E(U_1) - E(\ U_1) > 0) = F\ (x'\beta)$

The Heckman two-stage model uses a probit model for first stage equation. It assumes a cumulative normal distribution for $F\ (x'\beta)$ in equation (5). The second stage decision also called the intensity equation, specifies the extent of adoption of the soil sampling technology, given that adoption of the technology has already taken place $(y_i|\ d_i \ = 1)$. This equation is specified as equation 6 below:

(6) $y_i = E(y_i|\ d_i \ = 1) + v_i = \ x'_i\alpha + \varphi\widehat{IMR} + \ v_i \quad ; \widehat{IMR} = \ \phi(x'\beta)\ /\Phi\ (x'\beta)$

Model Assumptions:

(7) Exogeneity condition: $E(\varepsilon_i|x_i) = 0$ and $E(v_i|x_i) = 0$

(8) Joint Distribution: $(v_i\ , \varepsilon_i) \sim BVN\ (0, \tau)\ , \qquad \tau = \begin{bmatrix} 1 & \gamma \\ \gamma & \sigma^2 \end{bmatrix}$

In equation 6, the extent of adoption of the technology is a function of a set of producer/farm characteristics (x_i) as in the adoption equation and an error term, v_i. It is assumed that the explanatory variables in the both equations (5 and 6) are exogenous. This

assumption ensures that the estimated model parameters are consistent (Cameron and Trivedi, 2005). An important variable in the extent of adoption equation is the Inverse Mills Ratio, which a ratio of the standard normal probability density function , $\phi(x'\beta)$ and a standard normal cumulative density function $\Phi\ (x'\beta)$, both estimated from the first stage equation. This variable serves as a link between the two equations. The model parameters are captured by a vector β for the adoption equation, and a vector α and φ for the extent of adoption equation. The parameters will be estimated by using the Heckman two-step routine in STATA 14.

An important assumption of the Heckman two-stage model is that the first stage and second stage decisions are correlated (i.e. $\gamma \neq 0$) (Cameron and Trivedi, 2005). This assumption will be tested in this study. The two-part model which does not make any assumption on the correlation or otherwise of the first stage and second stage decisions will be used for this study, when the null hypothesis that $\gamma \neq 0$ is rejected statistically.

4.1. Data

This study will use the 2013 survey data on active cotton producers in 14 southern US states. The states included Alabama, Arkansas, Florida, Georgia, Kansas, Louisiana, Mississippi, Missouri, North Carolina, Oklahoma, South Carolina, Tennessee, Texas and Virginia (Xia et al. 2015). This survey was conducted by Cotton Incorporated, to know about cotton producers' perceptions and use of precision agricultural technologies. The questionnaire had questions on producer/farm characteristics, including questions on the year they started using georeferenced grid and zone management soil sampling technologies, the number of acres managed with these technologies, and other related information. The adoption or otherwise of the georeferenced grid soil sampling technologies describes the dependent variable that is used in the first stage decision equations. The number of acres managed with this technology will be used as the dependent variable in the second stage equations.

The questionnaire used for the survey was first pre-tested in July 2012, to modify the survey instrument (Xia et al. 2015). A mailing list of about 13,838 potential cotton producers within the 14-state survey region was obtained from the Cotton Board (Xia et al.

2015). Out of the list of 13,838 potential cotton producers, 13,566 producers were maintained, after 272 duplicate addresses, and the addresses of research and centers were removed. The questionnaires were sent out to the selected producers, with a postage-paid return envelope and a cover letter explaining the purpose of the survey. A response rate of 13.68 percent was achieved for this survey. This was calculated by the division of the number of usable responses (1,811) by the 13,237 (this number is the number of mailed questionnaires (13,566) minus the number of undelivered questionnaires due to incorrect addresses (66), and producers who had retired, were deceased or did not grow cotton (263) (Xia et al. 2015). A total of 75 individuals declined to participate in the survey. However, that number was included in the denominator for calculating the response rate, since reasons for their refusals to participate were not given (Xia et al. 2015). After data cleaning, a final dataset of 1344 complete responses will be used for this study.

4.2. Variable Descriptions and Hypothesized Effects

The explanatory variables used in this study are categorized into five main groups. They are producers' demographic and farm variables, economic variables, precision agriculture information sources, variables representing the usage of other precision agriculture technologies, and locational variables. For instance, under the demographic and farm characteristics, it is hypothesized that farmers with a bachelor's level education (and beyond) would be able to process information better (especially with respect to the potential benefits of soil sampling technology adoption) and influence producers to be more likely to adopt soil sampling technologies (McBride, 2003, Just et al. 2002). Also, younger farmers have longer planning horizons, and this attribute could have a positive effect on their adoption of soil sampling technologies and the extent of their adoption (Walton et al. 2010, Banerjee et al. 2008). It is expected that the greater the percentage of land owned relative to the total cultivated acreage, the less likely producers would be interested in the adoption and extent of adoption of soil sampling technologies. The hypothesized effect of percentage of land owned is also true for the producers' with less farming commitment. On the other hand, the percentage of land rented would show a commitment to farming. Therefore, it is expected that this variable would have a positive effect on the adoption and extent of adoption of soil sampling technologies. Livestock

ownership and the percentage of land devoted to other crops apart from cotton would show a reduced commitment to cotton production, and possibly a negative effect on the likelihood of adoption and extent of adoption soil sampling technologies. Cotton yield variability is anticipated to be directly linked to the variability of soil nutrients and other field attributes. Therefore, this variable is expected to have a positive effect on the adoption and extent of adoption of soil sampling technologies.

The economic variables, as described in Table 1, would be expected to have positive effects on the adoption and extent of adoption of soil sampling technologies, all things being equal. These variables are expected to raise the financial position of producers and positively affect their ability to buy and use these technologies (Banerjee et al. 2008). Therefore, the variables would have positive effects on the adoption and extent of adoption of soil sampling technologies. Another important variable that affects the adoption of agricultural technologies is varying agro-climatic zone and topography (Sunding and Zilberman, 2000, Winkelmann and Perrin, 1976). Thus, distance to input shops and other geographic locations are expected to have impacts on the adoption of agricultural technologies. Kenneth et al. 2010, using a survey data on cotton producers in the southeastern region of US and a count data method, show that the location of the farm is an important factor influencing the number of precision agriculture technologies adopted by cotton producers. Precision agriculture information is expected to reduce the potential information burden producers might face when they use precision agriculture technologies, like georeferenced soil sampling technologies (McBride and Daberkow, 2003). Precision agriculture information sources, in particular, crop consultants and farm input dealers, are expected to have a positive effect on the adoption of soil sampling technologies. But their direction of effect on the extent of adoption of these technologies is not clear. Producers' current use or experience in using complementary precision agriculture technologies are expected to positively influence the adoption of soil sampling technologies. The list of the explanatory variables in this study and their hypothesized effects are provided in Table 1.

Table1. Variable Description

Variables		
Demographic and Farm characteristics	**Hypothesis**	**Mean**
Grid soil sampling acreage		1398
Bachelor Education (dummy, equals 1 if bachelor or beyond, 0 otherwise)	+	0.179
Livestock ownership (dummy, equals 1 if yes, 0 otherwise)	-	0.25
Percentage of land devoted to other crops other than cotton	-	0.675
Percentage of land owned (equals, (total land owned/total farmed acreage) *100))	+	1.462
Number of years of farmer	-	54.66
Farming commitment (farm experience/number of years of farmer) *100))	+	48.91
Percentage of land rented (total landed rented/total farm acreage) *100))	+	0.018
Average *Yield Variability ((Dryland yield variability + Irrigated Yield Variability)/2)	+	329.5
Economic Factors		
Awareness of cost share reimbursements programs (CSP & EQIP) (dummy, equals 1 if true, 0 otherwise)	+	0.489
Income level above $150,000	+	0.111
Positive expectation of profit with precision agriculture (dummy, equals 1 if true, 0 otherwise)	+	0.896
Percentage income from farming	+	78.23
Receipts of cost share nutrient management program (dummy, equals 1 if true, 0 otherwise)	+	0.279

**Yield variability = cotton yield in productive land – Cotton yield least productive land.*

Table 1 continued. Variable Description

Information Sources (Dummy variables, equals 1 if the farmer used information source, 0 otherwise)	**Hypothesis**	**Mean**
University Extension	+	0.307
Crop consultant	+	0.439
Other farmers	+	0.625
Trade show	+	0.3
New media	+	0.136
Farm dealer	+	0.746
Precision Agriculture Technologies Used (Dummy variables, equals 1 if farmer used technology, 0 otherwise)		
Satellite Imagery	+	0.154
Yield Map	+	0.464
Electric Conductivity	+	0.139
Soil Survey Maps	+	0.318
Handheld GPS	+	0.2

4.3. Estimation and Inference

The Heckman Two Stage Selection Model is proposed to explain the adoption and the extent of adoption of grid soil sampling technology by cotton producers' in the southern US. The Heckman model accounts for potential sample selection bias when the modeler concentrates only on the positive acreage managed with the technology (Heckman, 1979). This is because the producers' decisions to adopt the soil sampling technology and the extent of adoption of the technology may be correlated (Heckman, 1979). Using this model, therefore, would ensure that the estimated model parameters are consistent (Heckman, 1979). The estimator uses the two-step variance estimator derived by Heckman to ensure that the standard errors are correct. Moreover, the null hypothesis of no sample selection bias will be tested using a t-test on the coefficient estimate of the Inverse Mills Ratio in the intensity equation (Heckman, 1979). This hypothesis also assumes that the first stage and second stage decisions of the producer are not related. If the null hypothesis is rejected at

least at the 10 percent level in both models, the Heckman model will be appropriate for the models (Heckman, 1979). Alternatively, the two-part model will be used if the null hypothesis is not rejected. A heteroscedastic consistent estimator, robust estimator, will be used for the two-part model estimator when they are used in this study. All the models in this study will be estimated with the Heckman and twopm STATA estimators for the Heckman and two-part models, respectively, whichever is the case.

Following Walton et al. (2010), the model assumes that producers' income above $150,000, cotton yield variability, the percentage of land devoted to other crops and percentage of income from farming are endogenous. A Rivers and Vuong (1988) approach will be used to simultaneously test for the exogeneity of the variables (the null hypothesis), and correct for endogeneity if the null hypothesis is rejected. At the first stage of the Rivers and Vuong (1988) approach, each endogenous variable will be regressed on all the other exogenous variables, including a set of instrumental variables. The instrumental variables that will be used are July humidity, July temperature, rural locality, farming-dependent locality, manufacturing-dependent locality, low education locality, and low employment locality. It is assumed that these variables are correlated with the endogenous variables (relevance assumption) and non-correlated with the equation error term (exogeneity assumption). The predicted residuals will be included as additional variables in the model. The null hypothesis of exogeneity will be tested by using an F-test to test the joint significance of the coefficients of the residuals in the model (Cameron and Trivedi, 2005). Also, the variance inflation factor approach will be used to check for multicollinearity among the explanatory variables in the models. A variance inflation factor of 10 or more will suggest multicollinearity might be a problem in the model (Walton et al. 2010). Multicollinearity will inflate the standard errors, but will not cause bias inferences (Cameron and Trivedi, 2005).

5. Results and Discussion

The null hypothesis of no sample selection bias is not rejected for the adoption and extent of adoption of georeferenced grid soil sampling technology, at a Z-value of 1.33. This means that the critical assumption of the Heckman's two stage selection model that the producers' decisions to adopt georeferenced soil sampling technology and the extent of adoption of the technology are correlated is rejected. Therefore, the model is estimated with the two-part model, which estimates the first and second stage equations separately with a probit model and ordinary least squares, respectively. As noted elsewhere in this study, this model is flexible and do not make any assumption on the correlation or otherwise of the first and second stage decisions of the producer concerning the use of the technology. Overall, the probit (first stage) and ordinarily least squares (second stage) models are both significant at the 1 percent level, with Chi-square values of 444 and 3.14, respectively. Moreover, the null hypothesis that producers' income above $150,000, cotton yield variability, the percentage of land devoted to other crops, income from farming are exogeneous is not rejected, at a chi-square value of 12 (p-value 0.12). A heteroscedastic consistent robust estimator was also used to estimate both equations in the Two-part model, to ensure reliable inferences from the model. Again, the variance inflation factors of all the explanatory variables are less than 10. This means multicollinearity is not a problem in the estimated two-part model.

The first stage adoption equation results show that producer's expectation of positive profits from precision agriculture, use of crop consultant as an information source, use of similar technologies such as yield map and soil survey maps, all have 1 percent significant and positive impacts on the likelihood of producers' adopting grid soil sampling technology. Moreover, average cotton yield variability, producers' awareness of cost share reimbursement programs, and the number of years of producers', all have 5 percent and positive impacts on the likelihood of the producer adopting the technology. Compared to producers in Virginia, producers in Florida, Mississippi, and Tennessee are more likely to adopt the technology. On the other hand, university extension has a negative impact on the likelihood of a producer adopting the technology, at the 5 percent significance level. The results above are provided in Table 2.

Table 2. Estimated Results of Georeferenced Grid Soil Sampling Model.

	First Stage (Probit)	Second Stage (OLS)
Demographic and Farm Characteristics		
Education (Bachelors and Beyond)	0.104	17.619
	(0.103)	(214.801)
Livestock ownership	0.111	438.935
	(0.139)	(287.951)
Percentage of land devoted to	-0.012	-41.742
other crops other than cotton	(0.014)	(28.34)
Number of years of farmer	0.014**	-5.736
	(0.007)	(13.688)
Average Yield Variability	0.001**	0.621
	(0)	(0.458)
Economic Factors		
Awareness of cost share reimbursements	0.224**	445.464**
programs (CSP & EQIP)	(0.106)	(218.638)
Income level above $150,000	-0.115	-175.67
	(0.153)	(341)
Positive expectation of profit	0.632***	-171.793
associated with precision agriculture	(0.154)	(393.398)
Percentage income from farming	0.003	12.966***
	(0.002)	(4.409)
Information Sources		
University Extension	-0.280**	110.258
	(0.118)	(255.097)
Crop consultant	0.312***	-67.831
	(0.118)	(236.799)
Other farmers	-0.036	-291.637
	(0.113)	(232.224)
Trade show	-0.131	-197.426
	(0.173)	(368.327)
New media	-0.16	201.568
	(0.142)	(323.297)
Farming input dealer	-0.186	-15.341
	(0.143)	(319.472)

***,**, ** denote significance at 1, 5 and 10 percent, respectively; values in parenthesis are standard errors.

Table 2 Continued. Estimated Results of Georeferenced Grid Soil Sampling Model

Precision Agriculture Technologies		
Satellite Imagery	0.001	426.224
	(0.268)	(476.678)
Yield Map	0.469***	907.113***
	(0.167)	(328.389)
Handheld GPS	0.183	-4.051
	(0.119)	(227.353)
Soil Survey Maps	0.419***	-625.497**
	(0.148)	(269.247)
Locational Factors		
Alabama	0.493	782.186
	(0.401)	(890.098)
Arizona	0.561	1254.851
	(0.567)	(1156.114)
Florida	1.203**	501.25
	(0.498)	(1025.129)
Georgia	0.049	339.441
	(0.42)	(928.754)
Kansas	0.179	-1412.339
	(0.587)	(1274.959)
Louisiana	0.653	333.417
	(0.444)	(973.536)
Missouri	0.543	364.356
	(0.456)	(952.901)

***,**, ** denote significance at 1, 5 and 10 percent, respectively; values in parenthesis are standard errors.

Table 2 Continued. Estimated Results of Georeferenced Grid Soil Sampling Model

Mississippi	1.033**	2167.273**
	(0.416)	(901.688)
North Carolina	0.485	1048.411
	(0.404)	(903.025)
Texas	-0.489	333.034
	(0.397)	(904.2)
Oklahoma	0.137	1149.66
	(0.639)	(1532.286)
South Carolina	0.192	616.755
	(0.43)	(946.706)
Tennessee	1.052**	614.663
	(0.42)	(922.677)
Constant	-4.354***	-1700.215
	(0.783)	(1680.69)
Number of Observation	1344	278
Log-likelihood	-462.7	-2422.8
Chi-square (Overall Model Significance)	444***	3.14***
[1]Exogeneity Test (Chi-square)	12.87 (P-value = 0.12)	
[2]Lambda (Heckman Model)	Z-statistic = 1790 (P-value=0.18))	

***,**, ** denote significance at 1, 5 and 10 percent, respectively; values in parenthesis are standard errors; [1]This is the parameter associated with the Inverse Mills Ratio in the Heckman's Model; [2]the lambda is the coefficient associated with the Inverse Mills Ratio in the estimated Heckman's Model.

The second stage model explains the extent of adoption of the technology conditional on the producer adopting the technology. The model results show that producers' awareness of a cost-share reimbursement program and percentage income from farming have positive effects on the extent of adoption of the technology, at the 5 and 10 percent significant levels, respectively (Table 2). Also, the use of yield maps and soil survey maps have positive and negative effects on the extent of adoption of the technology, both at the 1 percent significant level. Moreover, Table 3 shows that marginal effects of the variables in the two-part model. The marginal effects show the effects of the combined first stage (probit) and second stage (OLS) models. The results show that, producers' awareness of a cost-share reimbursement program, a 1 percent increase in the income from cotton production, and the use of yield map are expected to increase the acreage of land managed with the technology by 141.5, 3.30, and 291.1 units, respectively, all at the 1 percent significance level. Compared with producers in Virginia, a producer in Mississippi and Tennessee would increase the acreage managed with the technology by 676.1 and 360 units at the 1 percent and 10 percent significance levels, respectively. Also, a unit increase in average cotton yield variability would cause the producer to increase the land acreage managed with the technology by 0.25, at the 5 percent significance level. Again, ownership of livestock would increase the land acreage managed with the technology by 115.11 units, at the 10 percent level. However, a 1 percent increase in the land acreage devoted to other crops than cotton would cause the producer to decrease the acreage managed with the technology by 11.30 units.

Table 3. Marginal Effect Results

	Marginal Effects (Delta Method)	Standard Error
Demographic and Farm Characteristics		
Education (Bachelors and Beyond)	26.667	49.905
Livestock ownership	115.113*	67.109
Percentage of land devoted to other crops other than cotton	-11.229*	6.660
Average Yield Variability	0.245**	0.106
Number of years of farmer	1.994	3.196
Economic Factors		
Awareness of cost share reimbursements programs (CSP & EQIP)	141.463***	50.983
Income level above $150,000	-61.713	78.183
Positive expectation of profit associated with precision agriculture	104.536	87.841
Percentage income from farming	3.296***	1.011
Information Sources		
University Extension	-39.268	58.452
Crop consultant	55.113	55.148
Other farmers	-68.275	54.081
Trade show	-69.728	85.018
New media	6.296	73.649
Farming Input dealer	-44.249	72.922
Precision Agriculture Technologies		
Satellite Imagery	88.248	115.007
Yield Map	291.111***	77.533
Handheld GPS	39.632	53.783
Soil Survey Maps	-36.381	64.355

***,**, ** denote significance at 1, 5 and 10 percent, respectively.

Table 3 Continued. Marginal Effect Results

Locational Factors		
Alabama	270.645	204.195
Arizona	383.124	269.985
Florida	369.719	238.389
Georgia	80.968	213.116
Kansas	-252.001	293.632
Louisiana	213.375	223.219
Missouri	195.333	220.775
Mississippi	676.073***	208.469
North Carolina	323.832	206.641
Texas	-39.419	206.356
Oklahoma	267.555	346.506
South Carolina	169.839	217.455
Tennessee	359.695*	211.131

***,**, ** denote significance at 1, 5 and 10 percent, respectively.

6. Conclusion

This study investigated two issues concerning the adoption of precision agriculture in the southern US, using the two-part model. The two issues are the adoption and extent of adoption of georeferenced grid soil sampling technology. Producers' awareness of a cost-share reimbursement program, percentage of income from cotton production, the use of yield map, ownership of livestock, land acreage devoted to other crops, and cotton production in Mississippi and Tennessee have significant marginal impacts on the adoption and the acreage of land that is managed with the technology.

Soil sampling is seen as the foundation of precision agriculture. Therefore, the information above might be useful to extension services, agribusiness firms, and other stakeholders concerned with precision agriculture to reach out to producers who are likely to adopt georeferenced soil sampling technologies. Ultimately, this might help promote precision agriculture in the US.

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