MODELING THE CHOICE OF PRECISION AGRICULTURE INFORMATION SOURCE BY COTTON PRODUCERS IN THE SOUTHERN USA

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Abstract

Precision agriculture has the potential to improve the efficient use of agricultural inputs and the environment. But, in most cases the information required to allow producers to adopt this technology is limited. This study used a nested logit model to explain cotton producers' choice of precision agriculture information source. It estimated three models using the personal/impersonal, formal/informal, and public/private information source nests, with cross-sectional data from the 2013 cotton producer survey in 14 southern US states conducted by the Cotton Incorporated. The results of the study show that producers' perception of an information source is important in his/her information choice. Also, livestock ownership is important in influencing the producer to choose an impersonal, formal and a public information source. Moreover, producers in rural areas (population less than 2500), or have income above $150,000, or committed to farming are more likely to choose formal information sources. Again, compared to producers in Louisiana, producers in Missouri or Virginia are less likely to choose impersonal, formal and public information sources. The results of the study will be useful in helping relevant stakeholders in precision agriculture industry, to choose the appropriate information source to promote precision agriculture among agricultural producers in the US, in particular cotton producers.

Introduction

Historically, uniform application of inputs has been the main method of managing agricultural inputs on agricultural farms (Robert et al. 2000). Producers' used this input management strategy as an insurance against the possibility of plants not getting enough nutrients for their growth and other biological needs (Whelan and McBratney, 2000). But, this can be seen as an inefficient way of managing and applying agricultural inputs, which can also cause environmental deterioration from excessive use of inputs, especially fertilizers and pesticides and other inorganic chemicals (Robert et al. 2000). This input management strategy manages the variability within a field caused by heterogeneity in soil physiochemical properties to optimize input applications on agricultural lands (Cowan 2000). It has been suggested that this strategy could potentially mitigate against the concerns associated with the uniform application of inputs, specifically the inefficient use of farm inputs and environmental deterioration (Cowan 2000; Fountas et al. 2006; Robert et al. 2000).

The three main components involved in precision agriculture practices are information collection, data interpretation, and variable-rate application, using technologies such as Geographical Information Systems (GIS), Global Positioning Systems (GPS), Sensors, Variable Rate Technology (VRT) and Yield Monitoring (YM) (Bullock et al. 2002; Lowenberg-DeBoer, 2003; Rains et al. 2009). This makes the information requirement for this practice very intense and demands that producers exceed a certain precision agriculture information threshold to effectively adopt the practice (Fountas et al. 2006). But, in most cases the knowledge producers have on precision agriculture are below this threshold (Fountas et al. 2006). This implies that a deficit of precision agriculture information stock exists at the producer level that needs to be addressed for society to sustainably promote the adoption of this improved production technology. In the southern US, it has been shown that most farmers perceive other farmers, farm equipment sellers, crop consultants, university extension, news media, and government agencies as important sources of precision agricultural practices (Xia et al. 2015). However, McBride et al. (2003) acknowledges that a greater percentage of US farmers (about 70 percent of 8,400 US farms surveyed in 1998) are not aware of precision agricultural technologies. This raises a very critical question of the important factors producers consider when choosing a precision agriculture information source. With the exception of few studies such as Jenkins et al. (2002), most of the studies on producers' choice of agricultural information sources assumed that information sources are perfect substitutes (Ortmann et al. 1993, Schnitkey et al. 1992). This assumption is very restrictive and is likely not to hold in empirical research. This is because, studies have shown that agricultural information sources complement each other (Just et al. 2002, Roberts et al. 2010). This study will add to the precision agriculture information choice literature by explaining producers' choice of precision agriculture information sources, by taking into account the perceived correlation among information source alternatives. It is different from the others, like Jenkins et al. (2002), because it believes that information sources have natural groupings, called nests (Just et al. 2002). Ignoring the natural nesting structure of information sources might lead to a partial understanding of producers' information choice behavior. The study proposes to model producers' information choice behavior with a nested logit, which is seen as the ideal model for choice alternatives with a natural nesting structure (Cameron and Trivedi, 2005). Consequently, the primary objective of the study will be to investigate cotton producers' choice of precision agriculture information sources in the southern US. Specifically, it will identify the significant factors that determine the choice of an information source by cotton producers in the southern US. The southern US states in this study are Alabama, Arkansas, Florida, Georgia, Kansas, Louisiana, Mississippi, Missouri, North Carolina, Oklahoma, South Carolina, Tennessee, Texas and Virginia.

Materials and Methods

Conceptual Framework

As stated elsewhere in this study, the two main production technologies associated with cotton production are the uniform input management technology and the precision agriculture input management technology. It is assumed that producers' stock of knowledge or information on precision agriculture will be limited and in most cases not enough to enable a transition from a uniform input production technology to precision agricultural technology. Therefore, the potential benefit that will be associated with a given precision agriculture information source will depend on how it is able to bridge the potential information gap between the limited precision agriculture information of the producer and the information threshold required for the effective use of precision agricultural technologies. This benefit is an indirect benefit and it is highly dependent on how the adoption of precision agriculture through an information source will maximize farm profits. Also, there is a potential cost that is associated with the choice of an information source. The main costs are information search costs (including the opportunity costs of time), information consultation fees, and other costs. Over an expected precision agriculture adoption horizon T, the expected net present benefit (NPB) and the net present cost (NPC) of a precision agriculture information source (i) for a given cotton producer can be expressed as:

$$(1)\quad NPB = E\left\{\sum_{t=0}^{T}(A_{nj} - a_{nj})^t\right\} = \varphi(z,x)\,, \qquad j = 1, \dots, I$$

$$(2)\quad NPC = E\left\{\sum_{t=0}^{T}(s_j + cf_j + o_j)^t\right\} = \pi(z,x)$$

Where:

E: is an expectation formula, A_{nj} is the information threshold available to producer n for information source j; a_{nj} is the precision agriculture information source j available to producer n; s_j is the information search cost of the ith information source; cf_j is potential consultation fees of an information source; o_j is the other cost of information source j; $\varphi(z,x)$ is the functional form of expected net present benefit (NPB) : z and x are the information source and individual characteristics, respectively; $\pi(z,x)$ is the functional form of expected net present cost (NPC); I is the set of all feasible precision agriculture information sources.

The utility to the producer from the choice of a given information source is the difference between the expected net present benefit and the net present cost of the information source associated with the information source. This utility is a latent variable that guides the producer to select a restricted information source set of potential precision agriculture information sources (J) among all the feasible information sources that they can potentially choose from (I). Following the random utility framework, a cotton producer will choose an information source from the restricted information source set J when the utility associated with that information source is greater than that for other information sources in set J (Cameron and Trivedi, 2005).

This is expressed as:

$$(3)\ U_{nj}^{*} = V_{nj}(z,x) + \varepsilon_{nj} > U_{nk}^{*} = V_{nk}(z,x) + \varepsilon_{nk}\ , \quad j \neq k, \quad j \in J$$

Therefore, the probability that a producer will choose an information source j is:

$$(4)\ \Pr(y = j) = \Pr\{U_{nj} > U_{nk}\} = \Pr\{\varepsilon_{nk} - \varepsilon_{nj} < V_{nj}(z,x) - V_{nk}(z,x)\}$$
$$= F(z,x,\emptyset)$$

where:
U_{ni}^{*} is the latent utility to an individual n from choosing an information source j; V_{nj} is the deterministic component of the latent utility for alternative j: z and x are vectors of alternative specific and individual specific variables; ε_{nj} is the stochastic component of the latent utility for alternative j; $F(.)$ is a cumulative distribution function associated with the probability of choosing the information alternative j; $\emptyset$ is the set of parameters associated with the CDF, F(.).

Econometric Model

As noted by Cameron and Trivedi (2005), the nested logit is the ideal model to model choice situations where the alternatives follow a natural nesting structure. In this study, three precision agriculture information nesting structures will be modeled. The first nesting structure is the personal/impersonal/other information source nest (Gloy, Akridge and Whipker, 2002, Longo, 1990). Personal information sources include farm input dealers, crop consultants, university extension, other family members, and other farmers. The impersonal information sources are trade shows and the news media. The second nesting structure is the formal/informal/other (Just et al. 2002). The formal nest includes information sources such as crop consultant, university extension, trade show and news media, whiles the informal nest includes the farm input dealer, other farmers, and other family members. The last nesting structure is public/private/other (Just et al. 2002). The public nest includes information sources like university extension, trade show, and news media, while the private nest includes sources like farm input dealer, crop consultant, other farmers, and other family members. The study created another option called the “other”. The “other” option captures situations where producers did not make an information choice, chose two or more alternatives or chose alternatives across nests. The “other” option ensures that the alternatives in the information choice set within an information nest are mutually exclusive, exhaustive and finite (Train, 2003). An appropriate property of the nested logit model is that it allows for correlation or dependence of information sources within a nest but not across it (Cameron and Trivedi, 2005). That is, it relaxes the independence from irrelevant alternatives (IIA) assumption within a nest, but not across it. All the models will be estimated with a heteroscedastic robust estimator to ensure that inferences from them are valid (Cameron and Trivedi, 2005). Also, multicollinearity among the explanatory variables in the models will be checked using the variance inflation factors of the variables. Variance inflation factors less than 10 suggest that multicollinearity is not a problem in the model (Walton et al. 2010). Multicollinearity, when present, could inflate the standard errors of parameter estimates (Cameron and Trivedi, 2005).

The nested logit can be decomposed into two separate models. The upper model is a choice between information nests and the lower model is a choice among information alternatives within a nest. The nested logit model assumes that the CDF in equation (4) follows a generalized extreme value distribution (Cameron and Trivedi, 2005). This is also expressed as:

$$(5)\ F(z,x,\emptyset) = \exp[-G(e^{-\varepsilon_1}, e^{-\varepsilon_2}, \ldots, e^{-\varepsilon_J})]$$

According to Cameron and Trivedi (2005), to ensure that the joint probability density function and marginal density functions associated with equation (5) are well defined and sum up to one, the functional form G (.) is chosen to satisfy the following assumptions: non-negativity, homogeneity of degree one, mixed partial derivatives that are continuous and nonpositive for even order and nonnegative for odd order. This also ensures that the nested logit is consistent with the random utility theory. Given the above information, the combined utility (U_{ijk}) to a producer for choosing an information source j in nest k, and the associated probability are expressed in equations (6) and (7) below:

$$(6)\ U_{nj|k} = W_{nj|k}{}'\beta + V_{nk}{}'\alpha + \varepsilon_{nj}$$

$$(7)\ P_{nj|k} = P_{nj|k} * P_{nk} = \frac{\exp(W_{nj|k}{}'\beta)}{(\sum_{j=1}^{Jk}\exp(W_{nj|k}{}'\beta)} * \frac{\exp(\tau_k(V_{nk}{}'\alpha + IV_{nk}))}{\sum_{k=1}^{K}\exp(\tau_k(V_{nk}{}'\alpha + IV_{nk}))}$$

$$IV_{nk} = \ln\left(\sum_{j=1}^{J}\exp\left(W_{nj|k}{}'\beta\right)\right)$$

where:

P_{nk} is the probability that producer i chooses nest k; $P_{nj|k}$ is the probability that a producer chooses alternative j given that nest k is chosen; $\sum_{k=1}^{K}\tau_k = 1$ means that conditional logit suffices.

The parameters in the model (β, α, τ_k) are estimated by using a maximum likelihood approach with the "Nlogit" routine in STATA 14. This is achieved by maximizing the log-likelihood associated with equation (4), and it is obtained in the following steps:

$$(8)\ f(y_n) = \prod_{j=1}^{J}\prod_{k=1}^{K}[P_{nj|k} * P_{nk}]^{(y_{njk})} = \prod_{k=1}^{K}(P_{nk})^{y_{nk}}\prod_{j=1}^{J}(P_{nj|k})^{y_{nj|k}}$$

$$(9)\ \ln L = \sum_{i=1}^{N}\sum_{k=1}^{K} y_{nk} * \ln P_{nk} + \sum_{i=1}^{N}\sum_{k=1}^{K}\sum_{j=1}^{J} y_{nj|k} * \ln P_{nj|k}$$

Where:

y_{nk} is an indicator variable which equals 1 if nest k is chosen and 0 otherwise; $y_{nj|k}$ is an indicator variable which equals 1 if alternative j in nest k is chosen and 0 otherwise.

Data

The study will use a 2013 survey data on active cotton producers in 14 southern US states. The states are 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 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 427 usable responses will be used for this study. A detailed description of the variables used in estimating the models are provided in Table 1.

Table 1. Variable Description.

Demographic and Farm characteristics
Bachelor Education (dummy, equals 1 if bachelor or beyond, 0 otherwise)
Livestock ownership (dummy, equals 1 if yes, 0 otherwise)
Number of years of farmer (continuous variable)
Farming commitment (farm experience/number of years of farmer) *100))
Average Yield Variability ((Dryland yield variability + Irrigated Yield Variability)/2)
Distance to Input shop (continuous variable)
Live in a rural county (2500 or fewer people)
Live in a metropolitan county (>250000 people)
Live in a farming dependent county
Economic Factors
Awareness of cost share reimbursements programs (CSP & EQIP) (dummy, equals 1 if true, 0 otherwise)
Income level above $150,000 (dummy, equals 1 if producer used this source and zero otherwise)
Positive expectation of profit from precision agriculture (dummy, equals 1 if true, 0 otherwise)
Percentage income from farming (continuous variable)

Results and Discussion

This section first presents the results of the descriptive analysis of the pattern of precision agriculture information choice by cotton producers in the study. This is followed by the discussion of the results of nested logit model used to explain the choice of precision agriculture information.

Descriptive Analysis

The descriptive analysis results show that about 58 percent (248 cotton producers out of a total sample of 427 cotton producers) chose either a personal or an impersonal precision agriculture information source. For this group of producers, 82 percent (204 out of 248 producers) chose personal precision agriculture information source. Moreover, farm input dealer (other family members) was the most (least) preferred personal information source. For the personal information nest, most producers chose trade show information source. Similarly, with regards to the public/private/other information nest, about 58 percent (248 cotton producers out of a total sample of 427 cotton producers) chose either a public or private precision agriculture information source. Most of the producers choose the personal source of information (75 percent of 248), and 25 percent choose public information source. Again, for those that choose private information, the majority (minority) of producers choose farm input dealer (other farmers). Also, for the public information source, the most (least) choice information source is trade show (news media). Lastly, about 248 producers choose either a formal or an informal information source. Moreover, about 85 percent of the producers in this group chose a formal information source, and 15 percent the information source. With regards to the formal information source, the most (least) information source chosen is crop consultant (news media). For the informal information nest, the most (least) information source chosen is farm input dealer (other family members). For all the information nesting structures, about 42 percent (179 out of a total sample of 427 producers) fell into the "other" nest. This nest included producers who did not choose an information source, chose two or more alternatives within a nest or chose alternatives across nests.

Nested Logit Model Results

The null hypothesis that the inclusive values of the personal/impersonal/"other" nests, the formal/informal/"other nests, and the public/private/"other" nests are jointly equal to one are all rejected at the 1 percent level, with Chi-square values 111, 118 and 70, respectively, all with 3 degrees of freedom. This test result rejects the conditional logit model in favor of the nested logit model (Cameron and Trivedi, 2005). Also, the estimated nested logit model is consistent with the random utility model used to explain producers' choice of precision agriculture information source. This is because all the inclusive values for the personal/impersonal/"other" nests, the formal/informal/"other nests, and the public/private/"other" nests are all between 0 and 1. The inclusive value for the other option nest is constrained to take on a value of 1. Overall, all the estimated models are significant at the 1 percent level, with Chi-square values 5482, 2654, 5134, respectively, and all with 54 degrees of freedom. Again, multicollinearity is not a problem among the explanatory variables in this study. This is because the variance inflation factor of all the explanatory variables is below 4. For the lower model results for the three estimated models, the study shows that producers' perception of an information source has a positive effect (at the 1 percent significant level) on the likelihood of a producer choosing an information source (Table 2).

For the upper model results (Table 3) and for the personal/impersonal/"other" information nests, the estimated model results show that ownership of livestock has a positive effect (significant at the 1 percent level) on the probability of the producer choosing an impersonal information nest, compared to a personal information nest. Also, compared with producers in Louisiana, producers in Missouri or Virginia are less likely to choose an impersonal information nest compared to a personal information nest, at the 1 percent significance level.

Again, for the formal/informal/"other" nests model, the estimated model results show that producers' living in a rural county are more likely to choose a formal information source at the 10 percent level, compared to an informal information source (Table 3). This is contrary to the expectation of this study because producers in rural settings have more agricultural experience, are more self-reliable, and live "far away" from people, so they might rely on informal information sources than less rural people. Moreover, producers who are more committed to farming are more likely to choose a formal information source (Table 3). Also, producers who own livestock or whose income is above $150,000 are more likely to choose formal information sources compared to informal sources, at the 5 percent level (Table 3). Compared to producers in Louisiana, producers in Missouri or Virginia are less likely to choose a formal information source at the 1 percent level.

Moreover, for the public/private/"other" information nests, the estimated model results show that producers who own livestock are more likely to choose public information source than a private information source, at the 5 percent level (Table 3). Again, compared to producers in Louisiana, producers in Missouri or Virginia are less likely to choose a formal information source at the 1 percent level (Table 3).

Table 2. Lower Model: Choice alternative Within a Nest (Conditional Probability).

	Nested Logit Model 1 Impersonal/Personal/Other	Nested Logit Model 2 Formal/Informal/Other	Nested Logit Model 3 Public/Private/Other
Producer's Perception of an Information Source	0.259**	0.144	0.149
	(0.099)	(0.09)	(0.098)
Dummy for Impersonal Nest	-2.079*		
	(1.099)		
Dummy for Personal Nest	-2.028**		
	(0.875)		
Dummy Formal Nest		-1.922**	
		(0.976)	
Dummy for Informal Nest		-1.462*	
		(0.814)	
Dummy for Public Nest			-2.02*
			(1.114)
Dummy for Private Nest			-1.456*
			(0.834)
Number of observations at each level	427	427	427
Chi-square	5482.202***	2659.524***	5134.18***
Log-Likelihood Value	-655.518	-636.331	-644.727
BIC	1758.529	1720.155	1736.947
AIC	1421.036	1382.662	1399.454
Test inclusive values all equals 1 (Null Hypothesis)	111***	118***	70***

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

Table 3. Upper Model: Choice of Nests (Marginal Probability).

	Nested Logit Model 1 Impersonal/Personal/Other (Reference Nest: Personal)	Nested Logit Model 2 Formal/Informal/Other (Reference Nest: informal)	Nested Logit Model 3 Public/Private/Other (Reference Nest: Private)
Distance to an Input shop	0.0003	0.002	0.003
	(0.005)	(0.003)	(0.003)
Farming-Dependent County	-0.247	-0.021	-0.028
	(0.521)	(0.372)	(0.444)
Metropolitan County	-0.245	-0.139	-0.114
	(0.401)	(0.301)	(0.347)
Rural County	0.674	0.297*	0.733
	(0.487)	(0.4)	(0.431)
Number of years of the producer	-0.018	-0.011	-0.021
	(0.015)	(0.013)	(0.016)
Farming Commitment	0.015	0.008*	0.02
	(0.011)	(0.01)	(0.012)
Positive expectation of future profit from precision agriculture	-0.096	0.268	-0.12
	(0.353)	(0.292)	(0.327)
Average cotton yield variability	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)
Livestock ownership	0.975**	0.755**	0.986**
	(0.377)	(0.315)	(0.34)
Bachelor Education	-0.479	-0.236	-0.313
	(0.379)	(0.295)	(0.337)
Percentage income from farming	-0.009	-0.006	-0.007
	(0.007)	(0.005)	(0.007)
Income level above $150,000	0.373	1.212**	0.618
	(0.577)	(0.427)	(0.479)

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

Table 3 Continued. Upper Model: Choice of Nests (Marginal Probability).

Missouri Dummy	-13.528***	-0.396***	-13.604***
	(0.839)	(1.313)	(0.763)
Virginia Dummy	-13.811***	-13.967***	-14.017***
	(1.012)	(0.884)	(0.991)
Dissimilarity Parameters			
Impersonal Nest	0.174		
	(0.08)		
Personal Nest (Reference or base group)	0.267		
	(0.109)		
Formal Nest		0.137	
		(0.09)	
Informal Nest (Reference or base group)		0.123	
		(0.081)	
Public Nest			0.156
			(0.106)
Private Nest (Reference or base group)			0.15
			(0.102)
Other Nest	1	1	1
	(3.713)	(3.577)	(1.891)
Number of observations at each level	427	427	427
Chi-square	5482.202***	2659.524***	5134.18***
Log-Likelihood Value	-655.518	-636.331	-644.727
BIC	1758.529	1720.155	1736.947
AIC	1421.036	1382.662	1399.454
Test inclusive values all equals 1 (Null Hypothesis)	111***	118***	70***

***, **,* denote significance at 1, 5, and 10 percent, respectively; standard errors are in parenthesis, for conciseness all the state dummies that were not significant at the 10 percent level were omitted.

Summary

The study used the nested logit model to explain the choice of precision agriculture information source using three different information source nests. The nests were impersonal/personal/other, formal/informal/other, and public/private/other. The nested logit model was appropriate for this study. This is because, the null hypothesis that the parameters of the inclusive values of all the nest, in each nesting structure, are equal to 1 were rejected at the 1 percent level. These results eliminate the concern in the literature that, arbitrariness in forming nests (in the estimation of nested logit models) can affect the reliability of hypothesis test above (Greene, 2012). This also supports the statement from Cameron and Trivedi (2005) that the nested logit model is ideal for choice situations with natural nests, like the precision agriculture information source.

This study has shown that producers who might be rich (own livestock or have income above $150,000) are more likely to choose formal and impersonal information sources. To make sure all farmers, especially small scaled and with limited resourced producers, have access to precision agriculture information efforts should be made to enhance the outreach of university extension services (itself a formal information source) to them. This would ensure that small scale and resource poor producers also have access to better precision agriculture information. Moreover, the study showed that producers in rural areas prefer impersonal information sources. Information providers, in their bid, to reach this farming community, can to design effective communication content to educate them on precision agriculture information. The results of this study will be useful to precision agriculture information providers, precision agriculture equipment dealers, the Federal Government and other relevant stakeholders to target producers to promote precision agriculture.

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