A MULTINOMIAL LOGIT ANALYSIS OF THE ADOPTION OF COTTON PRECISION FARMING TECHNOLOGIES

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Abstract

Precision agriculture is gaining acceptance all over the world as a management strategy that increases the input use efficiency and reduces the negative environmental impacts of intensive agriculture production. Even with these advantages, the rate of adoption of precision agriculture practices is low in the US especially among the cotton producers. Using farm level data from the2009 Southern Precision farming Survey, this study analyses the farm and farmer characteristics that influence the adoption of specific variability detection technologies by the cotton farmers in the southern United States. A multinomial logit model with different technologies to detect field variability as choices was used to analyze the data. The results indicated that cotton farmers in Texas are less likely to adopt cotton yield monitor or employing a consultant to detect field variability, whereas   they are more likely to use soil survey maps compared to other southern states. Younger farmers with higher education and bigger farm size are more likely to adopt any of the variability detection practices. Farmers using computers for farming operations are more likely to adopt variability detection practices but are less likely to employ a consultant.   Annual household income of the farmer had significant positive impact on adoption of cotton yield monitor and employing a consultant.

Introduction

Precision agriculture is a farming method aimed at taking the right action at the right place at the right time. Natural and acquired variability in production capacity within the field implies that uniform agronomic management practices that are suitable for some parts of the field may be inappropriate in some other parts. To achieve the ultimate goal of sustainable cropping systems, variability must be considered both in space and time (Basso *et al.*, 2003). Precision management practices is in accordance with this principle and inputs application is done according to the need of the plant, taking into account the spatial and temporal variability in the field. Thus precision agriculture avoids excess application of inputs by limiting application to suit the field variability and hence also help in reducing the negative environmental impact.

The main objectives of precision agriculture are to increase the profitability of crop production and reduce the negative environmental impact by adjusting application rates of agricultural inputs according to local needs (Pierce and Nowark, 1990). The adoption of precision agriculture strategies is important not only to increase the profitability and sustainability of the farm, but also helps to protect the environment as the inputs are not applied in excessive quantities, which limits the potential of leaching of the chemicals to water streams. The components of precision agriculture technology are data collection, processing of data, and variable rate application of inputs (Blackmore *et al.,* 2003). Common variability detection practices include use of yield monitor, soil map, soil grid sampling, aerial photos, or satellite imagery to identify the variability in soil fertility, pH of the soil, crop vigor, or moisture stress. Once the variability within the field is detected and analyzed, this information is used to apply inputs like fertilizers, lime, pix or irrigation water in a way that each portion of the field receives the input in required quantities.

Even with all these potential advantages, the adoption of precision agriculture practices is low in the United States especially in cotton. The lower adoption rate of precision agriculture technology in USA can be attributed to the

lack of awareness of precision agriculture technology among the farmers (Daberkow and McBride, 2003), high cost of the technology, difficulty in proper understanding of the technology, and interpretation of the data (Reichardt and Jurgens, 2009). The study of the adoption of precision agriculture practices is very important to tide over the bottlenecks in adoption and to evolve efficient extension strategies.

In general, farmers decide on whether to adopt a new technology based on the economic benefit received from that technology, which in turn depends on the characteristics of the decision maker, and farm, crop markets, and the cost of the new technologies (Daberkow et al., 2002). Even though numerous studies were conducted to study the adoption of precision agriculture practices (Banerjee et al. 2008; Walton et al. 2008, Walton et al. 2010), most of those studies were aimed at studying the characteristics of the farm and the decision maker that influences the adoption of a particular variability detection technology or VRT. Since there are multiple technological choices available for the farmers to detect field variability, estimating the probability of a decision maker choosing to adopt a particular variability detection technology from different available technologies will provide a better understanding of the adoption behavior. Moreover, there is a need to compare the adoption patterns of Texas, the number one cotton producing state in the US, and other states; and of different regions within Texas.

This study examines the adoption of three different strategies for detection of field variability, namely yield monitor, soil survey maps and the help of a consultant. The adoption behavior of the farmers is then compared between other states and Texas and among 12 extension districts in Texas. The results from our study may help to identify the type of technologies more likely to be adopted by cotton growers and can be used to decide on further research initiatives. Identification of the factors affecting the adoption of the technologies can help the design of better extension strategies.

Materials and Methods

The Data
The data for this analysis are from the 2009 Southern Precision farming Survey (Mooney et al. 2010). This extensive survey received 1981 responses from cotton farmers in 12 southern states, of which 880 are from Texas. The survey provided information on the characteristics of the farmers, their farm, and their farming practices with special references to the different precision agriculture practices.

Empirical Model
A multinomial logit model was used to analyze the data. A multinomial logit model is a random utility model with discrete unordered choice sets that are mutually exclusive, exhaustive and finite. This model was used to estimate the probability of decision maker i choosing the alternative j (McFadden, 1974).

This model assumes that the decision maker will choose the alternative that provides him the highest utility from the available choice set. These utilities are unobservable but can be decomposed into a systematic observable part and an unobservable error part.

Then the utility received by farmer i by choosing technology j can be written as

$$U_{ij} = Z_{ij}\beta + \varepsilon_{ij}$$

Here $Z_{ij}\beta$ is the systematic or observed part of the utility and ε_{ij} is the unobservable error term. The term Z_{ij} is the vector of alternate specific characters that are hypothesized to influence the utility derived by the farmer. When we replace the unobservable utility term by decomposed terms, farmer i will choose technology j under the following condition.

$$Z_{ij}\beta + \varepsilon_{ij} \geq Z_{ik}\beta + \varepsilon_{ik} \quad \forall \quad j \neq k$$

Let the observed utility, $Z_{ij}\beta = V_{ij}$. Then the probability of farmer i by choosing technology j can be written as

$$P_{ij} = \frac{e^{V_{ij}}}{\sum_{j=1}^{J} e^{V_{ij}}}$$

For the empirical estimation of the model, different farm and farmer's characteristics are used as the independent variables and adoption of different field variability detection technologies are used as the choice set. The detailed description of the variables used in the study and the choice set are provided in table 1 and 2 respectively.

Table 1. The definition of variables used in the study

Number	Variable Name	Definition
1	TX	Farmers from the state of Texas
2	DIST1	Farmers from Texas Extension district 1 (Panhandle)
3	DIST2	Farmers from Texas Extension district 2 (South Plains)
4	DIST3	Farmers from Texas Extension district 3 (Rolling Plains)
5	DIST4	Farmers from Texas Extension district 4 (North)
6	DIST5	Farmers from Texas Extension district 5 (East)
7	DIST6	Farmers from Texas Extension district 6 (Far West)
8	DIST7	Farmers from Texas Extension district 7 (West Central)
9	DIST8	Farmers from Texas Extension district 8 (Central)
10	DIST9	Farmers from Texas Extension district 9 (Southeast)
11	DIST10	Farmers from Texas Extension district 10 (Southwest)
12	DIST11	Farmers from Texas Extension district 11 (Coastal Bend)
13	DIST12	Farmers from Texas Extension district 12 (South)
14	OTH	Farmers from states other than Texas
15	AREA	Average area planted to cotton in 2007 and 2008 in acres
16	AGE	Age of the decision maker in years
17	AGESQ	Square of the age of the decision maker
18	LIVESTOCK	Framers possessing livestock
19	EDUC	Number of years of formal education received by the farmer
20	COMP	Farmers using computers for farming operations
21	INC1	Farmers with annual income < $100,000
22	INC2	Farmers with annual income between $ 100,000 and $ 200,000.
23	INC3	Farmers with annual income > $200,000

Table 2. The definition of independent variable and choices used in the study

Number	Variable Name	Definition
1	TECH	The technology adopted by the decision maker
2	CON	Employing a consultant to detect variability
3	SOIL	Adoption of soil survey maps to detect variability
4	YM	Adoption of cotton yield monitor to detect variability
5	TOM	Adoption of 2 or more of the above practices
6	NON	Adoption of none of the above practices

Model Selection

An unrestricted model with all the individual specific variables (excluding the dummy variables DIST12 and Inc1 to avoid perfect multicollinearity) provided in Table 1 was used for estimation. Then different restricted models with fewer variables were used for empirical estimation of the model. From the results of these estimations, the Likelihood Ratio (LR) was calculated and likelihood ratio test was conducted to choose the best model. The LR statistic is calculated using the following equation

$$LR = 2(LL_{UR} - LL_R)$$

The different restricted models tried and the corresponding LR statistic is provided in Table 3. Model No.6 with 2 omitted variables (AGESQ and LIVESTOCK) was selected as it could exclude the largest number of variables without a significant LR statistic. From the results of the estimation with the empirical model, the marginal impact was calculated using the following equation.

$$\frac{1}{n}\sum_{i=1}^{n}\frac{dP_{ij}}{dI_i} = \frac{1}{n}\sum_{i=1}^{n}P_{ij}\left(\beta_j - \bar{\beta}_i\right)$$

where

$$\bar{\beta}_i = \sum_{j=1}^{J}P_{ij}\beta_j$$

Here the coefficient for the excluded alternative is set equal to zero for the calculation. The parameter estimates and marginal effects are provided below.

Table 3. The restricted models and corresponding LR statistic

No.	Model	LR
1	TECH~TX+DIST1+DIST2+DIST3+DIST4+DIST5+DIST6+DIST7+DIST8+DIST9+DIST10+DIST11 +LIVESTOCK+AGE+AGESQ+EDUC+COMP+INC2+INC3	27.1 **
2	TECH~TX+DIST1+DIST2+DIST3+DIST4+DIST5+DIST6+DIST7+DIST8+DIST9+DIST10+DIST11 +LIVESTOCK+AREA+AGE+EDUC+COMP+INC2+INC3	0.95 NS
3	TECH~TX+DIST1+DIST2+DIST3+DIST4+DIST5+DIST6+DIST7+DIST8+DIST9+DIST10+DIST11 +LIVESTOCK+AREA+AGE+AGESQ+EDUC+INC2+INC3	26.56 **
4	TECH~TX+DIST1+DIST2+DIST3+DIST4+DIST5+DIST6+DIST7+DIST8+DIST9+DIST10+DIST11 +LIVESTOCK+AREA+AGE+AGESQ+COMP+INC2+INC3	15.72 **
5	TECH~TX+DIST1+DIST2+DIST3+DIST4+DIST5+DIST6+DIST7+DIST8+DIST9+DIST10+DIST11 +AREA+AGE+AGESQ+EDUC+COMP+INC2+INC3	1.95 NS
6	TECH~TX+DIST1+DIST2+DIST3+DIST4+DIST5+DIST6+DIST7+DIST8+DIST9+DIST10+DIST11 +AREA+AGE +EDUC+COMP+INC2+INC3	2.9 NS
7	TECH~TX+DIST1+DIST2+DIST3+DIST4+DIST5+DIST6+DIST7+DIST8+DIST9+DIST10+DIST11 +LIVESTOCK+AREA+AGE+AGESQ+EDUC+COMP	13.3 **
8	TECH~TX+DIST1+DIST2+DIST3+DIST4+DIST5+DIST6+DIST7+DIST8+DIST9+DIST10+DIST11 +LIVESTOCK+AGE+AGESQ+EDUC+INC2+INC3	59.68 **
9	TECH~TX+DIST1+DIST2+DIST3+DIST4+DIST5+DIST6+DIST7+DIST8+DIST9+DIST10+DIST11 +AGE+AGESQ+EDUC+COMP+INC2+INC3	29.96 **
10	TECH~TX+DIST1+DIST2+DIST3+DIST4+DIST5+DIST6+DIST7+DIST8+DIST9+DIST10+DIST11 +AREA+AGE+EDUC+COMP	15.82 **
11	TECH~TX+DIST1+DIST2+DIST3+DIST4+DIST5+DIST6+DIST7+DIST8+DIST9+DIST10+DIST11 +EDUC+INC2+INC3	92.34 **
12	TECH~TX+DIST1+DIST2+DIST3+DIST4+DIST5+DIST6+DIST7+DIST8+DIST9+DIST10+DIST11 + AGE+AGESQ+EDUC	81.92 **
13	TECH~TX+DIST1+DIST2+DIST3+DIST4+DIST5+DIST6+DIST7+DIST8+DIST9+DIST10+DIST11 +EDUC	112.16 **
14	TECH~TX+LIVESTOCK+AREA+AGE+AGESQ+EDUC+COMP+INC2+INC3	90.24 **
15	TECH~TX+ AREA+AGE+AGESQ+EDUC+COMP+INC2+INC3	92.66 **

Results and Discussion

The results of the empirical estimation analyzing the impact of different geographical, farm and farmer characteristics on the choice of the variability detection technology by the cotton farmers are presented below.

Impact of Extension Districts
The estimates, standard errors, p values and marginal impact are provided for the three important extension districts in Texas as far as cotton farming is concerned (Panhandle, South Plains and Rolling Plains) in tables 4, 5, and 6. The results indicate that South Plains and Rolling plains have about 2.5 percentage points less likelihood to employ a consultant and 0.7 and 1.2 percentage points more likelihood to adopt soil survey maps compared to the south extension district of Texas. The panhandle area has about 1 percentage point higher adoption of two or more practices, but shows a 1.3 percentage lower adoption of soil survey maps compared to the south.

Table 4. The estimates, standard errors, p values and marginal impact for Panhandle

Practice	Estimate	SE	p	Marginal impact
CON	0.4537	0.1328	0.0007	0.03386
SOIL	-16.4975	<0.0001	<0.0001	-1.32454
YM	16.7941	0.0232	<0.0001	1.06286
TOM	-12.1612	<0.0001	<0.0001	-0.29461

Table 5. The estimates, standard errors, p values and marginal impact for South Plains

Practice	Estimate	SE	p	Marginal impact
CON	-0.5284	0.2398	0.0277	-0.2608
SOIL	11.4639	0.2769	<0.0001	0.7009
YM	15.9563	0.0797	<0.0001	0.7298
TOM	13.7868	0.1183	<0.0001	0.2562

Table 6. The estimates, standard errors, p values and marginal impact for Rolling Plains

Practice	Estimate	SE	p	Marginal impact
CON	-28.7032	<0.0001	<0.0001	-2.3856
SOIL	11.6588	0.1176	<0.0001	1.2859
YM	-20.0812	<0.0001	<0.0001	-0.9759
TOM	-10.6606	<0.0001	<0.0001	-0.1565

Comparison of adoption in Texas vs. other states

The estimates, standard errors, p values and marginal impact of Texas on adoption compared to other states are provided in Table7. Texas has a 3.7 percentage lower adoption of soil survey maps and 0.8 and 0.3 percentage lower likelihood of adoption of two or more practices and yield monitor respectively. The likelihood of employing a consultant is lower in Texas by 0.2 percentage points compared to other states. This result indicates the lower level of adoption of any kind of precision agriculture practice in Texas compared to other southern states in USA.

Table 7. The estimates, standard errors, p values and marginal impact for Texas

Practice	Estimate	SE	p	Marginal impact
CON	-1.3798	0.0976	<0.0001	-0.2046
SOIL	-48.6976	0.1128	<0.0001	-3.7221
YM	-8.5502	0.1278	<0.0001	-0.8157
TOM	-7.1923	0.1624	<0.0001	-0.2951

Effect of farm size

The estimates, standard errors, p values and marginal impact of farm size on adoption compared to other states are provided in Table8. Even though the area planted to cotton was significant in predicting the likelihood of adoption of two or more practices and yield monitor, the marginal impact was very low. A hundred acres increase in area planted to cotton is predicted to increase the likelihood of adoption of two or more practices by 0.002 percentage points only.

Table 8. The estimates, standard errors, p values and marginal impact of farm size

Practice	Estimate	SE	p	Marginal impact
CON	0.001	0.001	0.2096	0.0000059
SOIL	0.002	0.001	0.0615	0.0000096
YM	0.005	0.001	<0.001	0.0000223
TOM	0.005	0.001	<0.001	0.0000091

Effect of Age

The estimates, standard errors, p values and marginal impact of age of the decision maker on adoption of precision agriculture practices are provided in Table 9. Age, as expected, is predicted to have a negative impact on adoption of all of the technologies, but the marginal effects are very low. Older farmers are less likely to employ a consultant by a 0.0016 percentage for each year increase in age. Older farmers are likely to adopt soil survey maps 0.001 percentage lesser for each year increase in age. The likelihood of adoption of two or more technologies are also lesser for the older farmers at the rate of 0.001 percentage per year.

Table 9. The estimates, standard errors, p values and marginal impact of age of the decision maker

Practice	Estimate	SE	p	Marginal impact
CON	-0.0231	0.0060	<0.0001	-0.0162
SOIL	-0.0200	0.0067	0.0031	-0.0013
YM	-0.0241	0.0082	0.0034	-0.0009
TOM	-0.0095	0.0116	0.4146	-0.0014

Impact of Education

Education also has a positive impact on adoption of soil maps and on the adoption of two or more technologies. One more year of education increases the likelihood of adoption of soil maps by a 0.01 percentage and the likelihood of adoption of two or more practices by a 0.004 percentage. Against the general perception that more educated farmers will be more technologically capable and use less of the service of a consultant, the impact of education on the likelihood of employing a consultant was not statistically significant.

Table 10. The estimates, standard errors, p values and marginal impact of education of the decision maker

Practice	Estimate	SE	p	Marginal impact
CON	0.0330	0.0265	0.2126	0.0009
SOIL	0.1587	0.0285	<0.0001	0.0107
YM	0.1079	0.0350	0.0021	0.0043
TOM	0.0237	0.0531	0.6548	0.0002

Impact of use of computers

The famers who are using a computer for farm operations are less likely to employ a consultant by 0.03 percentage compared to those not using a computer. This is an expected result as the farmers using computers are more capable of performing the data analysis themselves. The famers who are using a computer for farm operations are more likely to adopt soil survey maps, yield monitor and two or more practices compared to the non adopters

Table 11. The estimates, standard errors, p values and marginal impact of use of computers

Practice	Estimate	SE	p	Marginal impact
CON	-0.1850	0.1983	0.3511	-0.0291
SOIL	0.5271	0.2232	0.0183	0.0290
YM	1.0643	0.2912	0.0003	0.0503
TOM	1.2502	0.4255	0.0034	0.0262

Impact of income

The effect of income for adoption was significant only for employing a consultant and adoption of yield monitor. This is as expected because only wealthy farmers can afford yield monitors and wealthy farmers are generally observed to utilize the service of consultants. The farmers with income higher than $200,000 are more likely to employ a consultant by a 0.03 percentage compared to farmers with income less than $ 100,000. Similarly, farmers with income higher than $200,000 are more likely to adopt yield monitor by a 0.01 percentage, compared to farmers with income less than $100,000.

Table 12. The estimates, standard errors, p values and marginal impact of INC 2

Practice	Estimate	SE	p	Marginal impact
CON	-0.2516	0.2363	0.2872	0.0247
SOIL	0.2174	0.2263	0.3367	0.0158
YM	0.3544	0.2663	0.1835	0.0189
TOM	-0.0963	0.2151	0.6543	0.0033

Table 13. The estimates, standard errors, p values and marginal impact of INC3

Practice	Estimate	SE	p	Marginal impact
CON	0.4614	0.2174	0.0339	0.0349
SOIL	0.1626	0.2498	0.5153	0.0051
YM	0.2383	0.2946	0.4187	0.0073
TOM	0.5503	0.2494	0.0275	0.0109

Summary

A multinomial logit model was used to analyze the 2009 southern precision farming survey to assess the impact of the farm and farmer characteristics on the adoption of different precision agriculture practices by the cotton farmers of southern United States. The results revealed that cotton farmers in Texas are less likely to adopt different precision agricultural practices. Farmer characteristics like age, education and income had considerable impact on the choice of variability detection technology. Farm size also significantly affected the choices, but the marginal impact was very small. Even though the general results are in agreement with the previous research findings, the strong assumption of independence from irreverent alternatives for the nested logit model may have a negative impact on the accuracy of the predictions of the model.

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