Adoption and Nonadoption of Precision Farming Technologies by Cotton Farmers

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Abstract

We analyzed data obtained from the 2009 Southern Cotton Precision Farming Survey of farmers in twelve states (Alabama, Arkansas, Florida, Georgia, Louisiana, Missouri, Mississippi, North Carolina, South Carolina, Tennessee, Texas, and Virginia) to identify reasons for adoption/nonadoption of precision farming technologies. Farmers provided cost, time constraint, satisfaction with the current practice and other as reasons for not adopting precision farming technology. Profit, environmental benefit and to be at the forefront of agricultural technology are main reasons for adopting precision farming technology. Results from a nested logit model indicated that formal education, farm size, and number of precision farming meeting attend by farmers have positive effect on adoption of PF technologies. Moreover, spatial yield variability increases probability of adopting precision farming technologies for profit reasons.

Keywords: adoption and nonadoption of technology, cotton, nested logit, precision farming

JEL Classification: C25, Q19

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1 Introduction

Precision farming (PF) is generally defined as a method capable of helping farmers to apply the right amounts of inputs, on right place, and at right time. Since its inception in mid 1980s, precision farming related technologies have been a common and growing occurrence in cereal and legume production. However, in cotton production, as our recent survey of farmers in twelve cotton growing states revealed, the adoption rate is only around 22%. This finding is surprising because precision farming technologies are generally touted to have both increased profit and environmental quality benefits. Precision farming technologies are used to obtain information about yield and soil characteristics at different points in a field. PF can potentially help farmers to establish a profitable crop management system and reduce environmental hazards by applying optimal inputs at different parts of the field (Bongiovanni and Lowenberg-DeBoer, 2004; Roberts et al., 2004; Torbett et al., 2007; Watson et al., 2005). It can also help to minimize production cost and maximize profit (Swinton and Lowenberg-DeBoer, 1998). Farmers who depend on profitability of practice evaluate returns from the adoption of technology ex ante. Uses of site-specific technologies are profitable in many crops (Griffin et al., 2004; Swinton and Lowenberg-DeBoer, 1998).

Precision farming is an important technology since it can reduce environmental burdens (Auernhammer, 2001). Farmers who are environmentally aware focus on the adoption of technologies that help to mitigate environmental hazards. For example, farmers who believe water quality is important are likely to adopt precision agriculture that helps to reduce water pollution. A desire to be at the forefront of agriculture technology could be a reason for practicing precision agriculture. Innovative farmers are likely to adopt PF at the beginning to take advantage of new technology (Lowenberg-DeBoer, 1996). Many studies have analyzed factors affecting the adoption of PF (Daberkow and McBride, 2003;

Larkin, 2005; Roberts et al., 2004; Pandit et al., 2011; Paxton et al., 2011; Paudel et al., 2011).

Adoption and nonadoption of precision farming (PF) depend on various factors. Farmers adopt technology for profit and/or to maximize utility (such as through better environmental quality). Reasons for nonadoption of PF are cost, satisfaction with the existing technology, time, and other reasons. Economic theory says that as long as an individual believes that benefits from adopting a technology exceed costs, the technology gets adopted. General understanding of perception of farmers reveal that farmers adopt a technology if it is in their best interest to adopt the technology. Farmers also have tendency to reject a technology at the beginning phase consistent with the typical technology adoption curve (only 2.5% farmers are innovative farmers). Yapa and Mayfield (1978) state that lack of sufficient information, lack of favorable attitude, lack of economic means to acquire technology and lack of physical availability of technology are the major cause behind nonadoption. Nowak (1992) provides the reasons for being unable or unwilling to adopt a conservation technology. He indicates that farmers are unable to adopt conservation technology because of lack of information, complexity of the system, high labor requirements, planning horizon for the technology to be profitable seem too far in the future, availability and inadequate managerial skill, lack of accessibility of supporting resources. For the reasons behind unwilling to adopt, we can classified these reasons as cost, satisfaction with the existing technology, time, and other reasons. So, behavioral characteristics of nonadopters could be very different than the characteristics of adopters. Knowing the answer to the question on why farmers adopt or do not adopt precision farming technologies can be helpful to formulate effective policies so that adoption rate can be increased.

The objective of the study is to identify reasons for adopting and nonadopting precision farming technologies by cotton farmers. We utilized data from the 2009 Southern Cotton Precision Farming Survey of farmers in twelve U.S. states and used a nested logit model to identify important variables.

2 Methodology

When a new technology is available, cotton producers may adopt or not adopt the technology. Cotton producers choose to adopt/not adopt based on some reasonings. In our case, cotton farmers decide to adopt PF technologies for three reasons and choose to not adopt PF technologies for four reasons. An appropriate model for this kind of data analysis is a nested logit. Nested logit model enables us to analyze the impact of independent variables on the choice of an alternative from a discrete, mutually exclusive, and exhaustive choice sets at different levels of decision making. We follow Heiss'(Heiss, 2002) utility theoretical framework to estimate the nested logit model (Cameron and Trivedi, 2010). At the first level, farmers' choose to adopt or not to adopt precision farming technologies. At the second level, farmers give reasons why they adopted or did not adopt the PF technologies. The tree structure of nested model is shown in figure 1. We assumed that response depends upon individual and farm characteristics.

Let's denote different alternatives by (j, k) where j denotes the decision to adopt or not adopt and k denotes the reason which is the mutually exclusive set of integers representing the available choice. Let the random utility model be

$$U_{jk} = V_{jk} + \epsilon_{jk} \qquad j = 1, 2. \qquad k = 1, ..., k_j \tag{1}$$

Where $k_1 = 3$ and $k_2 = 4$ and V_{jk} is linear predictor. The nested logit model assumes that ϵ_{jk} is distributed as a Gumbel's multivariate extreme-value distribution with the following distribution function.

$$F(\epsilon) = \exp\left(-\sum_{j=1}^{2}\left[\sum_{k=1}^{k_j}\exp\left(-\epsilon_{jk}^{1/\tau_j}\right)\right]^{\tau_j}\right) \tag{2}$$

Where τ_j is the scale parameter, which is a function of the correlation between ϵ_{jk} and ϵ_{jl}, and $\tau_j = \sqrt{1 - corr[\epsilon_{jk}, \epsilon_{jl}]}$. In our case all regressors are case specific so the linear predictor is

$$V_{jk} = z'\alpha_j + x'\beta_{jk} \tag{3}$$

Where z and x are the row vectors of explanatory variables for adoption decision and reasons respectively. α and β are their corresponding column vectors of regression coefficients and one of the $\beta_{jk} = 0$. The probability of adoption decision A and reasons R than can be expressed as

$$Pr(A = j) = \frac{\exp(z'\alpha_j + \tau_j I_j)}{\sum_{m=1}^{2} \exp(z'\alpha_j + \tau_m I_m)} \tag{4}$$

$$Pr(R = k/A = j) = \frac{\exp\left(x'\beta_{jk}/\tau_j\right)}{\sum_{l=1}^{k_j} \exp\left(x'\beta_{jl}/\tau_j\right)} \tag{5}$$

Where I_j is called the inclusive values and given by the following expression.

$$I_j = \ln\left\{\sum_{l=1}^{k_j} \exp\left(x'_j\beta_{jl}/\tau_j\right)\right\} \tag{6}$$

Let $i = 1, ..., N$ denotes the i^{th} farmers. Then y_{ijk} indicates that individual i chooses the j^{th} alternative in the first level, and k^{th} in the second level. Then the log likelihood for nested logit model is given as:

$$\begin{aligned} LL \;&=\; \sum_{i=1}^{N}\sum_{j=1}^{2}\sum_{k=1}^{j_k} y_{ijk}\left\{ z'_i\alpha_j + \tau_j I_{ij} - \log\left(\sum_{m=1}^{2} \exp(z'_i\alpha_j + \tau_m I_{im})\right)\right. \\ &\left. +x'_i\beta_{jk}/\tau_j - \log\left(\sum_{l=1}^{k_j} \exp\left(x'_i\beta_{jl}/\tau_j\right)\right)\right\} \end{aligned} \tag{7}$$

Parameters are estimated by maximizing the above log likelihood function.

3 Data

The data used was obtained from the 2009 Southern Cotton Precision Farming Survey collected from farmers in twelve U.S. States (Alabama, Arkansas, Florida, Georgia, Louisiana, Missouri, Mississippi, North Carolina, South Carolina, Tennessee, Texas, and Virginia). Survey method suggested by Dillman (2000) was used to collect information about precision farming technology adoption. Detailes on this survey are available in Mooney et al. (2010).

Farmers have provided three reasons (profit, environmental benefit, and the desire to be in the forefront of technology) for adopting PF technologies. There were four choices provided to farmers on why they decided not to adopt the PF technologies. Those reasons provided were i. Cost, ii. No time to adopt, iii. Satisfied with the current practice, and iv. Other. Fequency distribution of these reasons along with adopt/nonadopt are provided in Table 1. We found that 22.43% farmers (266 farmers) have adopted and 77.57% farmers (920 farmers) have not adopted cotton precision farming technologies. Among adopters 60.15% farmers provided profit as the reason, 21.80% farmers provided environmental benefit as the reason and 18.05% farmers provided to be at the forefront of technology as a reason for adopting precision farming. Among the reasons provided for nonadoption, cost was given as a reason by 46.41% of nonadopters, no time to adopt as a reason by 2.93% of nonadopters, satisfied with the current practice as a reason by 40.54% nonadopters and other unspecified reasons by 10.11% nonadopters.

The variables to explain the adoption/nonadoption for particular reasons are based on human capital theory, farm and production characteristics, and other variables used in precision farming adoption literature. Education and farming experience are measures of human capital that reflect the ability to innovate ideas. We expect that human capital has positive influence in the decision to adopt a new technology. Studies have shown that age has negative influence on technology adoption (Soule, Tegene, and Wiebe, 2000; Pandit et al., 2011; Paudel et al., 2011). Farm characteristics are important variable for understanding a farmer's decision to adopt (Pandit et al., 2011; Paudel et al., 2011). We also use financial and location variables as reasons for precision agriculture technology adoption. University publications are helpful to cotton producer to obtain precision farming information. Extension services convey information about university research and publication that help farmers to make informed decision which can influence profitability (Hall et al., 2003). Farmers with larger farms and higher than average county yield were more likely to adopt precision technology (Banerjee et al., 2008). Computer is essential to keep financial record and to find information about use of precision agriculture. It has been found that farmers who kept computerized financial records were more likely to be successful (Mishra, El-Osta, and Johnson, 1999). Knowledge of soil moisture variability in the field is helpful in reducing irrigation cost. McBratney et al. (2005) suggest beneficial role of precision farming in managing irrigation water. Paxton et al. (2011) studied the role of spatial yield variability on the number of precision farming technology adopted. They found that more within-field yield variability causes farmers to adopt precision farming technology. Although these studies provide some reasons for the adoption and nonadoption of precision farming technologies, there could be other possible variables affecting farmers' decision making process. Many farmers are uncertain to use available technology due to environmental regulations, public concerns, and economic gains from reduced inputs and improved managements, and hence these factors determine success of precision farming (Zhang, Wang, and Wang, 2002). Table 3 provides definitions and summary statistics for the variables used in empirical model.

4 Results

Percentage of farmers providing different reasons for adoption/nonadoption of precision farming technologies is given in Table 1 and Figure 2. We found that 36% cotton farmers did not adopt PF for cost reasons, which implies that cotton producers may have cash flow problem needed to buy specialized machinery. About 31.45% cotton producers are satisfied with the current practice(*satisfied*). Hence, many cotton producers do not want to adopt new PF at the beginning. Only 4.05% of cotton farmers adopt PF to be at the forefront of technology (*forefront*). This number is very small compared to the number of cotton producers who are satisfied with the current PF. It may imply that cotton farmers do not want to take risk from adopting PF. On the other hand, 13.49% cotton producers adopted PF for a profit reason. Only 4.89% practice PF for environmental benefit. Further, 2.27% cotton producers do not adopt PF because they stated time constraint as the reason for nonadoption (*time*) and 7.84% did not adopt due to other unspecified reasons.

We selected different set of variables that affects choice of level 1 (adoption/nonadoption) and level 2 (reasons). For level 1, we selected farm income, age, education, farm size, number of PF meetings attended by cotton producers. And for level two, we chose number of years of future farming plans, spatial yield variability, use of computer, farming information received from different sources, livestock, use of irrigation, and farmers' location being South Plains[1]. The definition and summary statistics of these variables are provided in Table 2.

The coefficients and marginal effects from nested logit model are provided in Table 3. Wald statistics of model significance and IIA test statistics are provided at the bottom of Table 3. The Wald test statistics is 145.62 which is highly significant indicating that overall model is valid. Further, the likelihood ratio test for IIA assumption is 11.91 which is highly signficiant favoring a nested logit model over a conditional logit model.

4.1 Adoption/Nonadoption

In the first level or adoption/nonadoption equation, we used nonadoption as a base category. Our results show that age has negative and significant effect on adoption of PF, which indicates that older cotton producers are less likely to adopt PF. We found that one year increase in age decreases the probability of adopting precision farming by 0.004. As we expected, we found that education is positive and significant, hence educated cotton producers are likely to adopt PF. The results indicate that one year increase in formal education increases the probability of PF adoption by 0.022. These findings are consistent

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[1] We consider regional effects based on five regions (Delta, Corn Belt, Appalachia, South East and South Plains). The model did not converge. As an alternative, we considered a dummy variable with farmers origin being South Plains. This is a logical choice as 41% of farmers in the dataset are from South Plains

with the finding of Paxton et al. (2011), Pandit et al. (2011) and Paudel et al. (2011).

We found that cotton farmers who have large farm size are likely to adopt PF. Marginal effects for farm size is 0.045 which indicates that if the farm size increases by 1000 acres, the likelihood of adopting precision farming increases by 0.045. This results is consistent with the results of Nair et al. (2011), Paxton et al. (2011) and Pandit et al. (2011). We found that cotton producers who participate in precision farming meetings are likely to adopt precision farming. This is true because if a cotton producer attends PF meetings he or she will gain knowledge about PF farming and adopt an appropriate PF technologies in his or her farm. Our results indicate if the number of PF meeting attended increased by one then the likelihood of of adopting PF increases by the 0.004.

4.2 Reasons behind adoption/nonadoption

For level 2, we choose cost as a base category as many cotton producers do not adopt PF because of high cost associated with machinery purchase. We interpret marginal effects in the text. Our finding suggest that a unit increase in spatial yield variability increases the probability of adopting PF for profit reason by 0.002. This results is consistent with the findings of Paxton et al. (2011) who reported that increased spatial yield variability promotes PF technology adoption. Further, our results indicate that cotton producers who use farming information from sources like university publications adopt PF not only for environmental benefit but also to be at the forefront of technology. Our results also indicated that cotton producers who are located at the South Plain region are less likely to adopt PF for profit, environmental benefit and to be at forefront of technology.

5 Conclusion

In this paper, we used a nested logit model to analyze factors associated with the adoption and nonadoption of PF technologies for various reasons. Our results showed that older farmers are less likely to adopt PF and educated farmers have more incentive to adopt PF technologies. We also found that farm size has positive effects on PF technology adoption. Number of PF meeting attendance increases the adoption of PF technology. Spatial yield variability results in higher probability of one adopting PF for profit reasons. In addition, our results also indicate that cotton producers who use farming information availble from university source are more likely to adopt PF for profit and to be at the forefront of technology adoption.

If a policy is needed to be formulated so that cotton farmers adopt precision farming technologies, then perhaps we should target educated farmers and large land holders. Making university easily available to farmers would have positive impact on PF adoption. County agents and county extension offices should make those university publications readily available to farmers. In particular we found that spatial yield variability on field makes farmers to adopt PF for a profit reason. Of course, these are preliminary results which need to be carefully looked at before developing a definitive policy to increase adoption rate of precision farming technologies in cotton production.

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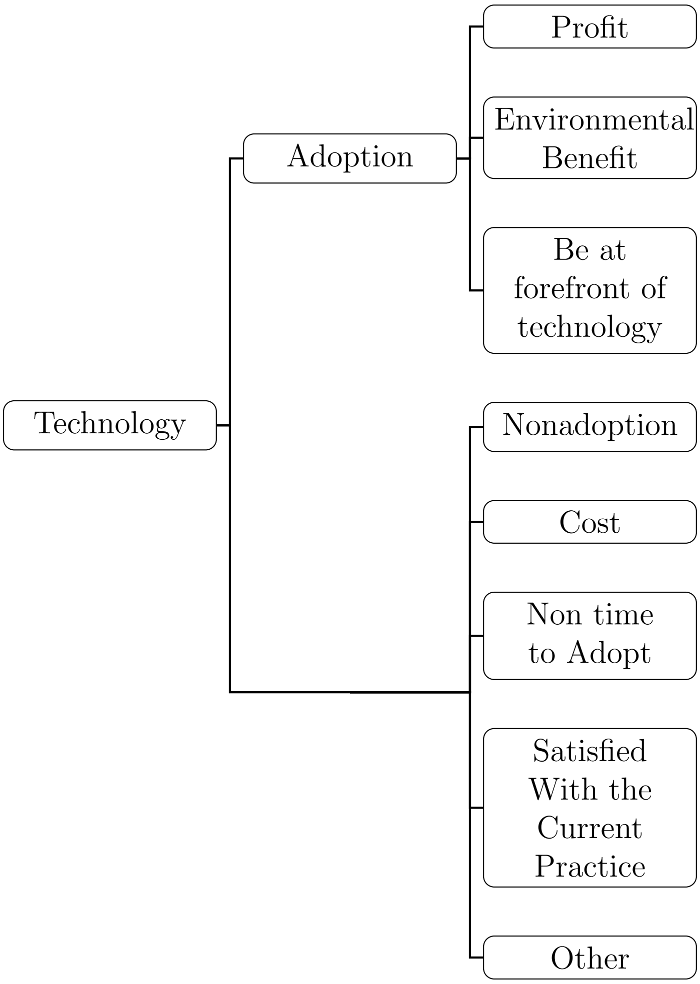

Figure 1: The tree structure for nested logit model

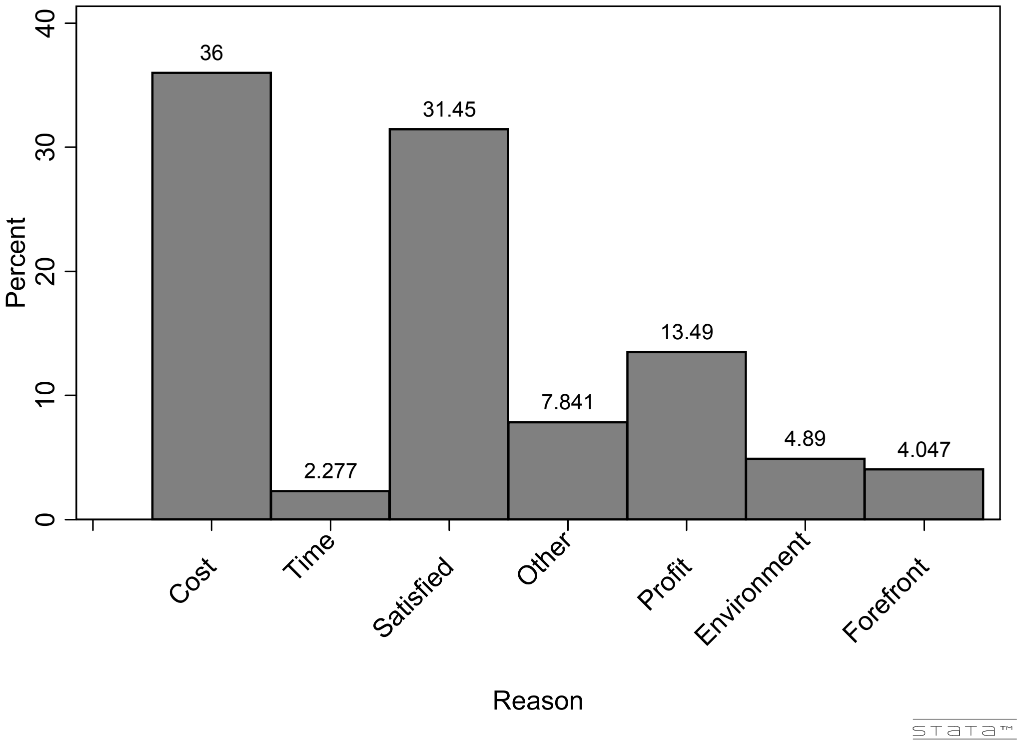

Figure 2: Percentage of cotton producers providing different reasons for adoption/nonadoption of precision farming technologies

Table 1: Frequency statistics of nested structure

	Adopt			Nonadopt			
Freq.	266			920			
%	22.43			77.57			
Reasons:	Profit	Environment	Forefront	Cost	Time	Satisfied	Other
Freq:	160	58	48	427	27	373	93
% Within label:	60.15	21.80	18.05	46.41	2.93	40.54	10.11
% Overall:	13.49	4.89	4.05	36.00	2.28	31.45	7.84

Table 2: Definition of variables and summary statistics

Variable	Definition	Obs.	Mean	SD
Farm plan (years)	Future plan of farming (years)	11249	3.743	1.55
Spatial yield variability	Spatial yield variability	8064	37.324	23.46
computer	=1 if farmers use computer for farm mangement	11102	0.539	0.50
Farming information	=1 if the farm uses university publication to obtain precision farming information	10906	0.349	0.48
Livestock	=1 if farmers own livestock	11578	0.333	0.47
Irrigation	Irrigation share acreage	11620	0.218	0.50
South Plains	=1 if farm is located in Southeast region (Texas), 0 otherwise	11648	0.446	0.50
Farm income	Percentage of farm income in total household income	10787	72.748	29.01
Age	Age of farm operators (years)	11067	53.883	12.67
Education	Formal education of farm operator	10612	14.189	2.53
Farm size	Farm size (000 acres)	11571	1.064	1.38
Number of PF meetings	Number of attendance in precision farming meeting	10437	2.818	6.01

Table 3: Parameter estimate and marginal effects of nested logit model

		Parameter Estimates		Marginal Effects
Level : equation	Variables	Coef	P-value	dy/dx
Level 1: Adoption	Farm income	0.006	0.13	0.001
	Age	-0.029	**0.00**	-0.004
	Education	0.145	**0.00**	0.022
	Farm size	0.298	**0.00**	0.045
	Number of PF meeting	0.025	**0.05**	0.004
Level 2: No time	Farm Plan (years)	-0.639	0.53	-0.011
	Spatial yield variability	-0.032	0.56	0.000
	Computer	-0.691	0.62	-0.012
	Farming Information	-0.011	0.99	-0.004
	Livestock	0.134	0.85	-0.001
	Irrigation	0.476	0.72	-0.001
	South Plains	-0.026	0.97	0.007
Level 2: Satisfied	Farm Plan (years)	-0.080	0.57	-0.006
	Spatial yield variability	-0.005	0.60	0.000
	Computer	-0.453	0.55	-0.096
	Farming Information	0.068	0.82	-0.038
	Livestock	0.331	0.55	0.030
	Irrigation	0.692	0.57	0.033
	South Plains	-0.027	0.91	0.095
Level 2: Other	Farm Plan (years)	-0.176	0.54	-0.008
	Spatial yield variability	-0.030	0.55	-0.002
	Computer	-0.260	0.66	-0.020
	Farming Information	0.087	0.86	-0.013
	Livestock	0.237	0.65	0.003
	Irrigation	0.732	0.61	0.010
	South Plains	-0.667	0.54	-0.006
Level 2: Profit	Farm Plan (years)	0.050	0.76	0.004
	Spatial yield variability	-0.013	**0.07**	0.002
	Computer	0.512	0.26	0.099
	Farming Information	0.515	0.35	0.105
	Livestock	0.286	0.51	0.008
	Irrigation	0.483	0.63	0.102
	South Plains	-1.978	**0.00**	-0.124
Level 2: Env.benefit	Farm Plan (years)	0.007	0.97	0.003
	Spatial yield variability	0.016	0.53	0.000
	Computer	0.938	0.31	0.027
	Farming Information	1.578	**0.04**	0.011
	Livestock	0.018	0.98	0.011
	Irrigation	1.146	0.16	0.023
	South Plains	-0.940	0.43	-0.079
Level 2: Forefront	Farm Plan (years)	-0.068	0.71	0.005
	Spatial yield variability	0.024	0.49	0.000
	Computer	1.224	0.18	0.018
	Farming Information	1.321	**0.08**	0.018
	Livestock	0.459	0.54	-0.002
	Irrigation	2.572	**0.07**	-0.015
	South Plains	-1.907	**0.03**	-0.045

Note: Log likelihood= -988.18 , Wald Chi-square= 145.62(**0.000**), LR test for IIA =11.91(**0.002**)
Bold P-value in table implies that the coefficients are significant at 10% level of significance.