Farmers' Perceptions about Spatial Yield Variability and Precision Farming Technology Adoption: An Empirical Study of Cotton Production in 12 Southeastern States

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Abstract

This paper examines how cotton farmers' perceptions about their spatial yield variability influence their decision to adopt precision farming technologies. Utilizing cross-section survey data from 12 Southeastern states and a two-step econometric modeling approach, we find that farmers who perceive their yields as more spatially heterogeneous will more likely use site specific information gathering technologies and apply their inputs at a variable rate. In addition, our empirical analysis shows that perceptions about future profitability and importance of precision farming, along with socio-economic factors, also drive the technology adoption decision. These results have implications for producers contemplating the variable rate management decisions, as well as dealers selling these precision farming technologies.

Keywords: Multinomial logit, endogeneity, variable rate input applications, site specific information gathering technology, yield perceptions

JEL Classification: Q12; Q16

1 Introduction

Large agricultural fields consist of numerous sites (or sub-locations) that typically differ from one another with respect to the factors that affect crop yields (i.e., different soil characteristics for different locations). Variable rate technologies (VRT) aim to take advantage of the heterogeneity within fields by allowing farmers to vary input applications depending on location-specific needs. By contrast, conventional farm management practices apply inputs at a single rate uniformly across the entire field, based on the average conditions in the field. If the responsiveness of yields to input varies substantially across a field, this average uniform application strategy can result in overapplication of inputs on some parts of the field and underapplication on other parts of the field. Thus, the VR applications can improve the efficiency of input application (Torbet et al., 2007) and may lead to increased profitability and environmental benefits, especially in fields that are spatially heterogeneous.

A prerequisite for successful implementation of the VRT is the use of site-specific information gathering (SSIG) technologies that enables one to determine the degree of spatial heterogeneity in fields. These SSIG technologies range from yield monitors to grid soil sampling and aerial imagery. Using spatially-referenced data from these site-specific technologies (e.g., nutrient content, soil quality, site-specific yields) allows one to apply varying input rates to match the spatial variability in the field. Although precision agriculture has been practiced since 1990s, the adoption rate is still very low in cotton production. This is due to expensive equipment costs, incompatibility between software, monitors and equipment; and repair delays (Lowenberg-DeBoer, 1998). Moreover, it was not until 2000, when USDA issued the first call for funding proposals for precision agriculture.

There have been previous studies that investigated factors influencing adoption of VR technologies using farm survey data and discrete choice modeling techniques (Fernandez-Cornejo, Daberkow, and McBride (2001); Khanna, Epouhe, and Hornbaker (1999); Khanna (2001); Roberts et al. (2004)). All of these studies aimed to determine farm (or farmer) characteristics (e.g., farm size, age, education, etc.) that significantly influence the adoption of VR technologies. Khanna (2001) and Roberts et al. (2004) assessed the impact of these farm characteristics within a framework that allows for sequential adoption of SSIG and VR technologies. Note that none of these studies specifically explored the role of farmers' perceptions about within-field spatial variability in the decision to adopt the VRT bundle.

The objective of this paper is to determine whether farmers' perceptions about their within-field yield variability significantly influence the decision to adopt precision technology. Previous literature has shown that the profitability of VR application technology critically depends on the degree of spatial variability in farmers' fields (Roberts, English, and Mahajanashetti, 2000; Isik and Khanna, 2002). Higher spatial variability typically results in higher economic returns from VR application. But in reality what really matters is the farmers' prior perception about spatial yield variability rather than the actual yield variability. For example, a farmer who has not used any SSIG technology may believe that the spatial variability of his/her field is low (i.e., believes that the field is more spatially homogenous) based solely on prior experience of farming the field (See Rejesus et al., 2010 for evidence of this behavior). Hence, this particular farmer may decide not to adopt the VRT bundle because he/she believes that the potential economic returns from this investment may not be worth it due to the perceived lack of spatial heterogeneity (even if the field is, in reality, spatially heterogeneous).

Examining whether spatial yield variability perception affects VRT adoption behavior is consistent with recent literature that advocates the use of subjective perceptions in empirical models explaining economic behavior (Nyarko and Schotter, 2002; Manski, 2004; Bellemare, 2009). As Delavande, Gine, and McKenzie (2009) have shown, there are a number of studies in the agricultural economics literature that demonstrate how subjective perceptions influence decision-making in agriculture. For example, Hill (2007) found that subjective expectations about future coffee prices influence the allocation of labor used in coffee production. Gine, Townsend and Vickery (2008) reveal that farmers' perceptions about the start of the monsoon season affect their planting decisions even after controlling for a wide-range of farmer characteristics. The role of perceptions has also been examined in a number of technology adoption studies as well (Gould, et al., 1989; Adesina and Zinnah, 1993; Adesina and Baidu-Forson, 1995; Sall et al., 2000; Abadi Ghadim, Panell, and Burton, 2005). But note that most of these technology adoption studies investigate the influence of perceptions about the attributes of the technology itself and not the effects of perceptions about another factor that determines profitability of the technology (i.e., VR applications). To the best of our knowledge, no study has yet investigated the impact of perceptions about a spatially explicit variable in the adoption of agricultural technologies (SSIG) and the variable rate management decisions. Our paper contributes to the literature in this regard.

2 Estimation Strategy: Multinomial Logit

We estimate a multinomial logit model (MNL) where the dependent variable (precision farming technology or Y_i) is discrete and takes the values of 1, 2 and 3 respectively. The explanatory variable of interest ($Perceptions_i$) is continuous and endogenous. Thus, we first perform a first stage estimation (OLS) of $Perceptions_i$, and then use its predicted values as instruments in the second stage MNL model. More specifically,

$$Perceptions_i = \alpha_1 W_i + e_i \tag{1}$$

where W_i is a vector of control covariates (that include instrumental variables) and e_i is an error term. The cross-sectional nature of our data, along with the fact that unobserved characteristics included in education, age, etc. might affect the perceptions' formation, imply possible measurement error. Therefore, the predicted value of $Perceptions_i$ is then utilized in MNL instead of the actual $Perceptions_i$ to account for this potential endogeneity caused by unobserved variables that influence both perceptions and precision technology adoption. The use of (1) in the estimation requires good instruments correlated with $Perceptions_i$, but uncorrelated with the unobservables that affect precision farming adoption (embodied in e_i). Without any strong instruments, the inferences from our estimation must be interpreted with caution. The two-step procedure described below and the use of predicted values necessitate the use of bootstrapped standard errors (1000 replications), since the conventional standard errors would be incorrect.

Cotton farmers are now considered as consumers of agricultural technologies, who have to choose between the following precision farming options: *alternative 1*: no adoption of any site-specific information gathering technology (SSIG) or variable rate technology (VRT), *alternative 2*: adoption of at least one SSIG technology and input application at a uniform rate (URT), and *alternative 3*: adoption of at least one SSIG and input application at a variable rate (VRT).

Let $U_{i,None}$, $U_{i,SSSIG-URT}$, and $U_{i,SSIG-VRT}$ denote i producer's expected utility from choosing between the unordered choices *1*, *2* and *3* respectively. The observed variable in this case is the technology choice decision Y_i, where

$$Y_i = 1 \text{ if } U_{i,None} > U_{i,SSIG-URT} \text{ and } U_{i,None} > U_{i,SSIG-VRT}$$
$$Y_i = 2 \text{ if } U_{i,SSIG-URT} > U_{i,None} \text{ and } U_{i,SSIG-URT} > U_{i,SSIG-VRT}$$
$$Y_i = 3 \text{ if } U_{i,SSIG-VRT} > U_{i,None} \text{ and } U_{i,SSIG-VRT} > U_{i,SSIG-URT}$$

Each farmer's expected utility is assumed to be a function of observable covariates x_i, plus a random disturbance that captures non modeled effects. We model her choice using a multinomial logit, which is an extension of the binary logistic regression but has more than two values for the dependent variable. Since we cannot identify separate b's for all of the choices, we set the coefficients for one of the outcomes (i.e., the reference alternative) equal to one (Jones, 2000). Hence, the probability of a farmer i to choose an alternative j is given by:

$$P_{i,j} = P(Y_i = j) = \frac{exp(x_i b_j)}{1 + \sum_{j=1}^{m} exp(x_i b_j)} \tag{2}$$

and the choice probability for the base is

$$P_{i,j} = P(Y_i = 1) = \frac{1}{1 + \sum_{j=1}^{m} exp(x_i b_j)} \tag{3}$$

where x_i is the vector of independent variables associated to farmer i, and b_j is the vector of parameters associated to the alternative j. In our case, the non adoption of SSIG and VRT may be treated as the baseline category. The multinomial logit model, which also accounts for the simultaneity of choices, would identify the probability of using SSIG and applying inputs at a uniform rate relatively to the non adoption as well as the probability of using SSIG and applying inputs at a variable rate relatively to the non adoption. The estimated parameters of a multinomial logit are even more difficult to interpret than those of a bivariate choice model. To capture the effect of the explanatory variables on the farm management decisions, we examine the derivative of the probabilities with respect to the explanatory variables. These derivatives are defined as (Greene 1990):

$$\frac{\partial Prob(Y_i = j)}{\partial x_{ik}} = P_j[\beta_{jk} - \sum_{m=0}^{2} Prob(Y_i = m)\beta_{jk}] \tag{4}$$

The above relationship demonstrates the marginal effect of on the probability of adopting either one of the scenarios 1, 2, and 3.

We calculated both the average marginal effects AME (i.e., the marginal effects on the probabilities for each observation and then take the average of it), as well as the marginal effects at the average MEA (i.e., marginal effects on the probabilities of each independent variable calculated at the means of each independent variable). Studies have shown though, that evaluating the derivatives at their sample means leads to biased predictions, plus they are restricted to discrete explanatory variables.

Multinomial logit method is computationally simpler than other approaches (e.g., multinomial probit), but it relies on the very restrictive assumption of independence of irrelevant alternatives (IIA)[1]. This property states that the probability of choosing among two alternatives is not affected by the presence of additional alternatives . Otherwise MNL is not appropriate and we should implement other nested models e.g. nested logit[2].

3 Data

Data for this study were collected from a survey sent to cotton producers in 12 states: Alabama, Arkansas, Florida, Georgia, Louisiana, Mississippi, Missouri, North Carolina, South Carolina, Tennessee, Texas and Virginia. This survey was developed to query cotton producers about their attitudes toward and use of precision farming technologies (i.e., SSIG and VRT). Following Dillman's (1978) general mail survey procedures, the questionnaire, a postage-paid return

[1]The basic idea of the Hausman test is to estimate the model with all the alternatives and then to re-estimate it dropping one of the alternatives. After dropping *alternatives 2*: (SSIG and URT) and *3*: (SSIG and VRT), the chi (squared) statistics are -4.71 and 6.85, respectively. Thus, we fail to reject IIA.

[2]We also estimated the model using a multinomial probit (computationally more complicated, but relaxes the IIA assumption), and our results are consistent with the multinomial logit.

envelope, and a cover letter explaining the purpose of the survey were sent to each producer. The initial mailing of the questionnaire was on February 20, 2009, and a reminder post card was sent two weeks later on March 5, 2009. A follow-up mailing to producers not responding to previous inquiries was conducted three weeks later on March 27, 2009. The second mailing included a letter indicating the importance of the survey, the questionnaire, and a postage paid return envelope. A mailing list of 14,089 potential cotton producers for the 2007-2008 marketing year was furnished by the Cotton Board in Memphis, Tennessee. Among responses received, 1981 were counted as valid, and thus used in our study.

Our survey consisted of three main sections: 1. precision agriculture technology (i.e., sources of information about technology, ways of inputs application, expectations, etc.), 2. farm and production data (i.e., farm location, acres of owned and/or rented land, yields per acre etc.), and 3. socioeconomic characteristics (age, experience with farming, education level, income etc).

Only 35% of the valid responses indicated use of at least one SSIG technologies (some producers made use of more than one technologies), and around 22% applied their inputs at a variable rate. The most popular SSIG technologies were the grid and zone soil sampling, followed by the yield monitors with GPS. The most used variable rate management decisions were fertility or lime, and then followed the growth regulator. Less than half of respondents are high school graduates and almost 25% have a bachelor's degree. Most of the farmers' income ranges from \$50,000 to \$99,000 annually, whereas 10% of cotton producers in our survey have income above \$500,000.

4 Variable Construction and Empirical Specification

Based on the estimation strategy above, we constructed the necessary dependent and independent variables using responses from the survey questionnaire. Farmers were asked to indicate the acres on which five information gathering technologies (i.e., yield monitoring with GPS, aerial satellite, handheld GPS units, green seeker and electrical conductivity) were used in order to make the variable rate decision (i.e., drainage, lime, seeding, growth regulator, fungicide, herbicide, irrigation etc). A producer who provided an answer for this question[3] was considered both an SSIG and VRT adopter (Y_i=3).

SSIG and URT adopters are those who checked either one of the cotton yield monitors, grid sampling, soil maps, satellite imagery, aerial photography or COTMAN technologies, but did not provide an answer to the above question regarding VRT decisions (Y_i=2).

[Place Figures 1 and 2 here]

The $Perceptions_i$ variable is calculated based on their answers about the least productive, average productive and most productive sections of the farmer's field. We then utilize the spatial variability formula used in Larson and Roberts (2004) to calculate perceived Spatial Yield Variability (SYVAR):

$$SYVAR = 0.33 * (Y_{LOW} - Y_{AVG})^2 + 0.33 * (Y_{MID} - Y_{AVG})^2 + 0.33 * (Y_{HIGH} - Y_{AVG})^2 \quad (5)$$

where Y_{LOW} is the best estimate for the yield of the least productive portion of field, Y_{AVG} is the estimated average yield for the typical field, Y_{HIGH} is the estimated yield for the most productive portion and Y_{MID}=3Y_{AVG} - Y_{LOW}. We, then, used the SYVAR and Y_{AVG}, in order to create a coefficient of spatial yield variability ($SYCV_i$) statistic based on the following formula:

$$SYCV = \frac{SYVAR_i^{0.5}}{Y_{AVG}} 100 \quad (6)$$

where $SYVAR_i^{0.5}$ is the standard deviation of spatial yield variability estimated using (5).

[Place Figure 3 here]

4.1 Explanatory Variables for SSIG and VRT

From the literature review, we identified the factors affecting the precision farming adoption decisions and we created proxy variables, based on the availability of our sources. Since SSIG

[3]There was a small fraction of farmers who answered "don't know". We included them in the adopters' category as well, because they might have not been aware of the exact number of acres where they utilized VR practices.

and VRT are considered as a bundle of technologies, rather than a single unit, the explanatory variables included in *alternative 2* (SSIG and URT) were also used in estimating *alternative* 3 (SSIG and VRT)[4]. The farmer characteristics, assumed to affect technology decisions, were the level of their education, year they were born, the use of computer in farm management, the percentage of taxable income from farming, perceptions about future importance and profitability of precision farming, manure application, soil quality, yields, and location dummies.

We would expect that producers with a bachelors or a graduate degree (COLLEGE) will most likely adopt a new technology because of the human capital and the technical skills that they have acquired through their education. Younger farmers (AGE) are expected to be more familiar with the new technologies, thus more likely to adopt precision farming. On the other hand, they are less experienced, which implies that they might not be aware of their field variability contrary to the older ones, thus not eager to adopt new technologies. Hence, the sign cannot be determined a priori. The use of computer is hypothesized to have a positive effect on precision farming, since it is part of the farm management and can also be considered as a proxy for innovativeness (Surjandari I., and Batte M., 2003). To capture the effect of income in technology adoption, we used a proxy variable that accounted for the percentage of the 2007 taxable household income coming only from farming, contrary to the different categories of pretax total household income from both farm and nonfarm sources (Banerjee et al., 2008). We would expect that the higher this percentage, the higher the probability of adopting new technology, in the sense that farmers who make a living mostly by farming will invest on practices that would improve their harvests and hence their profitability (INCOME).

Moreover, we incorporated farmers' perceptions about future profitability of precision farming as well as future importance. We would expect that farmers who argue that precision farming will be important 5 years from now (IMPORTANCE), as well as those who believe that its use will be more profitable in the future (PROFIT), would more likely adopt SSIG and VRT technologies. We added proxies of MANURE, YIELDS (Khanna, 2001), as well as 12 dummies (AL, AR, FL, GA, LA, MS, MO, NC, SC, TN, TX and VA) that capture the effect

[4] We faced a similar situation when applying the 2-step Heckman approach. In practice, it is very difficult to find plausible identification restrictions, in which case the Heckman model is estimated with the same set of regressors in each equation. Then, identification relies on the non-linearity of inverse mills ratio (A. Jones 2001, Cameron A. and Trivedi P., 2005)

of farm location on VRT adoption. We cannot make hypotheses for the regions' signs in advance. Regarding the impact of actual yields, we would expect that a higher average cotton lint yield (YIELDS), which is a possible indicator of land quality, may imply positive effect on the probability of adopting VRT. The effect of manure on VRT is expected to be rather negative. Farmers who use manure might have lower incentives to adopt VRT, compared to those who rely on inorganic fertilizers (Khanna, 2001). Regarding the variable of interest ($\widehat{SYCV}$), we would expect a positive sign. Farmers, who perceive that their yields are more variable, would more probably utilize information gathering technologies, in order to better see their true within field variability. Likewise, they would more possibly apply their inputs at a variable rate.

4.2 Instruments for Yield Risk Perceptions

For the vector W_i , we included two instrumental variables – the 10-year county average yields and the total acreage (sum of rented and owned acres) of the previous year (2007). The 10-year county average (PINDEX) may be a good instrument since it is publicly available information that gives a benchmark to individual producers as to where their field may stand in comparison to the county (NASS, USDA). Hence, we posit that it influences perceptions about spatial variability but is not correlated with farm-level unobservable variables. The sign of PINDEX is ambiguous and depends on how farmers see their fields in high or low yielding areas. Regarding the total acreage (FARM SIZE) previous studies have indicated a positive relationship between the farm-size and the spatial within field yield variability. Therefore, we would expect that producers who operate large farms will believe that their yields are more variable.

5 Results and Discussion

The first stage of perceived spatial yield variability regression indicated significant coefficients and sensible signs. Farmers in high yielding areas perceive that their yields are more homogenous, whereas farmers with large acreage believe that their yields are more variable. F statistic which represents the joint significance of the two exogenous variables is high.

[**Place Table 2 here**]

We use the "non adoption" (category 1) as reference point. Under this scenario, our predictions for perceived yield variability have the expected signs and are statistically significant for all three categories. Farmers, who perceive their yields more variable, they will probably utilize SSIG and/or VRT. Farmers, who perceive their yields more homogeneous (i.e., more optimistic farmers), will most probably not utilize any type of SSIG technology, and thus VR applications. This result is robust with all the specifications we applied.

Scenario 2: SSIG and URT

Table 3 shows the coefficients and the standard errors of the MNL approach, along with the marginal effects of the explanatory variables. We estimate the marginal effects since the coefficients in MNL are simply the values that maximize the likelihood function and do not have a direct interpretation. The conditional probability of adopting at least one SSIG technology with uniform rate input applications was significantly and positively related (0.6%) with the predicted spatial yield variability perceptions ($\widehat{SYCV}$), the year that producer was born (AGE), the use of computer in farm management (COMPUTER) and the perception about future importance of precision farming (IMPORTANCE).

Younger farmers, who are more innovative, and those who believe that information gathering technologies will be important in five years, will more likely (0.1%) utilize these techniques. On the other hand, the perceptions about future profitability (PROFIT) seem to inversely affect the use of information gathering technologies and the uniform rate input application. Farmers who believe that the new technology will be less profitable in the future will probably use SSIG technologies but apply their inputs at a uniform rate (8%). Although, they might access their true yield variability through SSIG, they are reluctant to purchase VRT, if they consider precision farming potentially non profitable.

Bachelor's or graduate degree (COLLEGE), along with manure application (MANURE) have a negative albeit insignificant impact on SSIG and URT. We would expect that users of organic fertilizer would have more incentives to apply their inputs at a uniform rate, thus a positive sign. Similarly, we would expect that more educated farmers would more likely adopt SSIG technologies, but maybe the negative effect from URT offsets the positive effect of college on SSIG. Actual yields (YIELDS), the percentage of taxable income coming only from farming sources (INCOME), and the soil quality have the consistent from literature positive signs, but they do not strongly affect farmers' decision to adopt SSIG and use URT. Regarding the location dummies, the effect is either positive or negative but insignificant for all cases. The negative signs in farm locations might be an implication that remote locations, far from a regional center and the available equipment, will less likely adopt precision technology.

[**Place Table 3 here**]

Scenario 3: SSIG and VRT

The same explanatory variables that were utilized above seem to have a stronger effect for the farmers who used at least one SSIG technology and decided to apply VRT afterward. More educated (COLLEGE) and younger (AGE) farmers, who use computer (COMPUTER) and believe that precision agriculture will be profitable in the future (PROFIT), and whose income comes mainly from farming (INCOME) will more likely use the precision farming bundle by 7%, 0.2%, 11%, 12% and 0.1% respectively. Contrary to the previous alternative estimation, expected future profits positively affect the probability of adopting SSIG along with VRT. The same holds for farmers whose taxable income comes mainly from cotton farming. Although it is not statistically significant, the effect of actual yields on adoption decision is negative. The interpretation could be that high yields reflecting high land quality do not necessarily imply high yield variability, thus no incentive for producers to utilize VRT.

The positive and significant coefficient of the PROFIT variable is indicative of the importance of the profit maximizing decision in farmer's behavior. The probability of using a new technology is higher for those who believe that this technology would bring profits in the near future (i.e., 5 years from now). Likewise, COLLEGE is a significant determinant of VRT adoption, since the information revealed from SSIG technologies would be more evident to a well educated farmer, who is familiar with soil properties.

Our marginal effects are consistent with Roberts et al. (2004) and Khanna (2001) for the majority of the explanatory variables. However, we should not ignore the fact that our variables are constructed using survey questions, thus differences in the signs might result from the differences between the data.

[**Place Table 4 here**]

6 Conclusions

Applying a multinomial logit model, we tried to infer about the role of perceived yield variability in the precision farming decision. Our results suggest that farmers who perceive that their yields are more variable, will most likely apply their inputs at a variable rate. This is consistent with the theoretical insight in Isik and Khanna (2002) who found that higher spatial variability increases the incentive to adopt precision technologies. Another approach we implemented was the 2-step Heckman correction model, which presumes that producers' decision about precision technology is sequential. We first estimated the SSIG adoption using the full sample of farmers (i.e., adopters and non-adopters), and then appended an inverse mills ratio to VRT adoption estimation, which referred to the selected sample of precision technology adopters. Our findings are identical with this method as well.

This has important implications for agribusiness firms and VRT sellers. Since the perceived yield variability of SSIG adopters leads to higher conditional probability of VRT adoption, then VRT dealers may have incentives to offer free information gathering technologies so that farmers can better see their true within field variability.

Future research could involve incorporation of additional data from previous surveys. Although, respondents are different, we might infer whether farmers' perceptions regarding yields affect technology adoption decision in a similar way. We could also include perceived yield variability into a more general context of perceptions, i.e., how yield perceptions, along with perceptions about future profitability and perceptions about future importance of precision agriculture, affect SSIG and VRT adoption (i.e., use of a Tobit model, see Adesina Forson).

References

[1] Abadi Ghadim A., Panell D.J., and Burton M.P., "Risk, uncertainty, and learning in adoption of a crop innovation", *Agricultural Economics*, Volume 33, Issue 1, p.p. 1-9, July 2005.

[2] Adesina A., and Baidu-Forson J., "Farmers' perceptions and adoption of new agricultural technology: Evidence from analysis in Burkina Faso and Guinea, West Africa", *Agricultural Economics*, Volume 13, Issue 1, 1995.

[3] Banerjee S.B., Martin S.W., Roberts R.K., Larkin L.S., Larson J.A., Paxton W.K., English B.C., Marra M.C., Reeves M.J., "A Binary Logit Estimation of Factors Affecting Adoption of GPS Guidance Systems by Cotton Producers", *Journal of Agricultural and Applied Economics*, 40,1 (April 2008):345-355.

[4] Bellemare M.F., "When Perception is Reality: Subjective Expectations and Contracting", *American Journal of Agricultural Economics*, 91 (Number 5, 2009): 1377-1381.

[5] Cameron C.A., Trivedi P.K., "Microeconometrics: Methods and Applications", Cambridge University Press, 2005.

[6] Delavande A., Gine X., and McKenzie D., "Measuring Subjective Expectations in Developing Countries: A Critical Review and New Evidence", *Journal of Development Economics*, 2010.

[7] English B.C., Mahajanashetti S.B., Roberts R.K., "Assessing Spatial Break-even Variability in Fields with Two or More Management Zones", *Journal of Agricultural and Applied Economics*; 33, 3 (Dec.2001): 551-565.

[8] Fernandez-Cornejo, J., Daberkow S.G., and McBride W.D., "Decomposing the Size Effect on the Adoption of Innovations: Agrobiotechnology and Precision Farming", *AgBioForum* 4 (2001): 124-36.

[9] Gine X., Townsend R., and Vickery J., "Rational Expectations? Evidence from Planting Decisions in Semi-Arid India", Working Paper No.166, *Bureau for Research and Economic Analysis of Development (BREAD)*, March 2008.

[10] Gould, B.W., Saupe, W.E., and Klemme, R.M. (1989). "Conservation tillage: The Role of farm and operator characteristics and the perception of soil erosion", *Land Economics*, 65, 167-82.

[11] Greene WH., "Econometric anlyisis", 5th Edition, Prentice Hall, NJ USA, 2003.

[12] Griffin T.W., Lowenberg-DeBoer J., Lambert D.M., Peone J., Payne T., Dabercow S.G., "Precision Farming: Adoption, Profitability, and Making Better Use of Data", Site Specific Management Center (SSMC) Purdue University and USDA-ERS.

[13] Hausman J. and Mc.Fadden D., "Specification Tests for the Multinomial Logit Model", Econometrica 52: 1219-1240, 1984.

[14] Hill, Ruth Vargas (2006) "Coffee Price Risk in the Market: Exporter, Producer and Trader Data from Uganda", Mimeo. IFPRI.

[15] Isik M., Khanna M., "Uncertainty and Spatial Variability: Incentives for Variable Rate Technology Adoption in Agriculture", *Risk Decision and Polic*y, vol.7. pp. 249-265, 2002.

[16] Jones A. "Applied Econometrics for Health Economists", 2nd Edition Office of Health Economics (OHE).

[17] Khanna M., "Sequential Adoption of Site Specific Technologies and its Implications for Nitrogen Productivity: A double selectivity model", *American Journal of Agricultural Economics*, 83 (2001), 35-51.

[18] Khanna, M., Epouhe O.F., and Hornbaker R. "Site-Specific Crop Management: Adoption Patterns and Incentives", *Rev. Agr. Econ.*, 21 (1999): 455-472.

[19] Larson J.A and Roberts R.K, "Farmers' Perceptions about Spatial Yield Variability as Influenced by Precision Farming Information Gathering Technologies", Selected Paper

presented at annual meeting of the Southern Agricultural Economics Association, Tulsa OK, February 14-18 2004.

[20] Manski C., "Measuring Expectations", *Econometrica*, Vol.72 No.5 (1329-1376), September 2004.

[21] Marra M.C., Rejesus R.M., Roberts R.K., English B.C., Larson J.A., Larkin S.L., Martin S., "Estimating the Demand and Willingness to Pay for Cotton Yield Monitors", *Precision Agric.*, DOI 10.1007/s11119-009-9127-z.

[22] Mooney D.F., Roberts R.K., English B.C., Lambert D.M., Larson J.A., Velandia M., Larkin S.L., Marra M.C., Martin S.W., Mishra A., Paxton K.W., Rejesus R., Segarra E., Wang C. and Reeves J.M., "Precision Farming by Cotton Producers in Twelve Southern States: Results from the 2009 Southern Cotton Precision Farming Survey", Research Series 10-02 Dept. of Agricultural and Resource Economics, The University of Tennessee, May 2010.

[23] Nyarko Y., and Schotter A., "An Experimental Study of Belief Learning Using Elicited Beliefs", *Econometrica*, Volume 70 Issue 3, p.p. 971-1105, May 2002.

[24] Rejesus R.M., Marra M.C., Roberts R.K., English B.C., Larson A.J., Paxton W.K., "Changes in Producers' Perceptions of Within-Field Yield Variability Following Adoption of Cotton Yield Monitor", Selected Paper prepared for presentation at the Agricultural and Applied Economics Association 2010 AAEA, Denver Colorado, July 25-28 2010.

[25] Roberts R.K., English B.C., Larson J.A., Cochran R.L., Goodman R.W., Larkin S.,L., Marra M.C., Martin S.W., Shurley W.D., Reeves J.M., "Adoption of Site Specific Information and Variable Rate Technologies in Cotton Precision Farming", *Journal of Agricultural and Applied Economic.*, 36,1 (April 2004): 143-158.

[26] Sall S., Norman D., and Featherstone A.M., "Quantitative assessment of improved rice variety adoption: the farmers' perspective", *Agricultural Systems*, Volume 66, Issue 2, p.p. 129-144, November 2000.

[27] Torbet J.C., Roberts R.K., Larson J.A., English B.C., "Perceived importance of precision farming technologies in improving phosphorus and potassium efficiency in cotton production", *Precision Agriculture* (2007) 8:127-137, DOI 10.1007/s11119-007-9033-1.

7 Appendix

Table 1: Summary of dependent and independent variables used in the OLS and the Multinomial Logit Model

Variable	**Description**	**Mean**	**StD**
SYCV	Perceived Spatial Yield Variability	30.74727	1.331025
PINDEX	Soil productivity index using 10-year county yields as a proxy (US Dept. of Agriculture, National Agricultural Statistics Service, 2010)	644.5297	6.028936
FARM SIZE	Total acreage (sum of rented and owned acres) for 2007 crop season	325.8354	36.36688
SSIG	Farmer used at least one site-specific information gathering technology (yes=1; no=0)	0.2412923	0.0096156
VRT	Farmer applied her inputs at a variable rate (yes=1; no=0)	0.3219424	0.0198324
COLLEGE	Farm operator had either a bachelors' or a graduate degree (yes=1; no=0)	0.4021739	0.0124027
AGE	Age of the farm operator (in terms of year born)	1953.166	0.3187948
IMPORTANCE	Farmer perceived that precision farming would be important in five years from now (yes=1; no=0)	0.6971227	0.0103266
PROFIT	Farmer perceived that precision farming would be profitable to use in the future (yes=1; no=0)	0.4316002	0.011131
COMPUTER	Farmer uses computer for farm management (yes=1; no=0)	0.5378606	0.4987144
INCOME	Percentage of 2007 taxable household income coming only from farming sources	71.7231	0.7795698
YIELDS	Estimate of average yield per acre for 2007 crop season	1166.337	30.94584
MANURE	Farmer applied manure on his/her fields (yes=1; no=0)	0.2481013	0.0217594
SOIL QUALITY	Ratio of historical yields over average yields	1.764122	17.791
AL	Farm located in Alabama (yes=1; no=0)	0.0636042	0.0054845
AR	Farm located in Arkansas (yes=1; no=0)	0.0413932	0.0044766
FL	Farm located in Florida (yes=1; no=0)	0.0989399	0.0067101
GA	Farm located in Georgia (yes=1; no=0)	0.0161535	0.0028331
LA	Farm located in Louisiana (yes=1; no=0)	0.0449268	0.0046552
MS	Farm located in Mississippi (yes=1; no=0)	0.0726906	0.0058347
MO	Farm located in Missouri (yes=1; no=0)	0.022211	0.0033119
NC	Farm located in North Carolina (yes=1; no=0)	0.0959112	0.0066177
SC	Farm located in South Carolina (yes=1; no=0)	0.0307925	0.0038824
TN	Farm located in Tennessee (yes=1; no=0)	0.0560323	0.0051685
TX	Farm located in Texas (yes=1; no=0)	0.4457345	0.0111703
VA	Farm located in Virginia (yes=1; no=0)	0.0116103	0.0024074

Table 2: OLS Results of the SYCV Estimation

Variable	Coefficient	P-Value
INTERCEPT[1] ***	47.91679	0.000
PINDEX ***	-0.0244354	0.000
FARM SIZE **	0.0028964	0.002
$No. Observations = 961$		
$R^2 = 0.0308$		
$F(2, 958) = 15.23$		

[1] $*$, $**$, and $***$ denote significance levels at a 10%, 5% and 1% respectively

Figure 1: **SSIG Variable Construction**

16. How do you assess the yield variability *within* a typical cotton field on your farm? (Check all that apply)
Cotton yield monitor ____________ Grid sampling ___________ Year-to-year field records ________
Soil maps ______________ Consultants' estimates _________ Satellite imagery ________________
Aerial photography ________ COTMAN ________ Other (specify) ___________________________

Figure 2: **VRT Variable Construction**

17. For each variable rate cotton management decision in the left column of the table below, indicate the acres on which the five information gathering technologies were used to make the variable rate decision. Leave blanks where the technology was not used. (Provide your best estimate.)

Variable Rate Decision	1. Yield Monitoring with GPS	2. Aerial/Satellite Infrared Imagery	3. Handheld GPS Units	4. Green Seeker	5. Electrical Conductivity (for example, Veris, Soil Doctor)
Drainage					
Fertility or Lime					
Seeding					
Growth Regulator					
Harvest Aids					
Fungicide					
Herbicide					
Insecticide					
Irrigation					

Figure 3: **SYCV Construction**

15. Yields vary within a field. Give your best estimate for *cotton yields* (lbs. lint/acre) for the following portions of your **typical field**:

For Dryland: Least productive 1/3 _____ Average productive 1/3 _____ Most productive 1/3 _____

For Irrigated: Least productive 1/3 _____ Average productive 1/3 _____ Most productive 1/3 _____

Table 3: SSIG Adoption and URT

Variable	**Coefficient**	**Bootstrap Std. error**	**Marginal Effects at the average(MEA)**	**Delta-method Std. error**	**Average Marginal Effects (AME)**	**Delta-method Std. error**
INTERCEPT [1]*	-42.86858	16.49892	—	—	—	—
$\widehat{SYCV}$ *	0.0744289	0.0310317	0.0090216	0.00459	0.0065179	0.0038911
COLLEGE	0.1346293	0.1957773	-0.0012192	0.03132	-0.0093144	0.0275637
AGE **	0.0195077	0.0086617	0.0023943	0.00131	0.0017462	0.0011463
YIELDS	0.000342	0.0003117	0.000057	0.00004	0.0000497	0.0000381
SOIL QUALITY	0.0806175	0.1787759	0.0100589	0.0199	0.0074246	0.0150999
IMPORTANCE **	0.6708316	0.2565062	0.0884399	0.03814	0.0782774	0.0435933
PROFIT **	-0.2851806	0.2308274	-0.081424	0.03281	-0.0848116	0.0281061
INCOME	0.0047271	0.0034917	0.0003702	0.00052	0.0001564	0.0004589
COMPUTER **	0.550945	0.2129616	0.0530783	0.03167	0.0311699	0.0284104
MANURE	0.0361645	0.2586485	-0.0009382	0.03947	-0.0032613	0.0347114
AL	-0.2254715	1.659936	-0.0283781	0.10049	-0.021643	0.0954872
AR	-0.083342	2.685451	-0.0198078	0.12889	-0.0201017	0.1209622
FL	-1.094505	4.134595	-0.1304284	0.08348	-0.1466263	0.1425303
GA	-0.1570056	1.661377	-0.0525006	0.08909	-0.0558905	0.0921669
LA	0.9560014	1.695277	0.1177788	0.14706	0.0904489	0.102623
MS	0.368846	1.596986	0.0371884	0.11698	0.0264389	0.0946633
MO	0.2330897	1.798793	0.0401154	0.15267	0.0327845	0.1195139
NC	0.0963116	1.667366	0.0129053	0.10268	0.0098863	0.0877612
SC	0.9922796	1.615526	0.1580759	0.15329	0.1144274	0.102269
TN	-0.1846223	1.707552	-0.0303271	0.0995	-0.0279797	0.0952835
TX	-1.44405	1.709179	-0.1457761	0.08897	-0.1007573	0.0915857
VA	(omitted)	—	—	—	—	—

[1] $*$, $**$, and $***$ denote significance levels at a 10%, 5% and 1% respectively

Table 4: SSIG Adoption and VRT

Variable[1]	**Coefficient**	**Bootstrap Std. error**	**Marginal Effects at the average(MEA)**	**Delta-method Std. error**	**Average Marginal Effects (AME)**	**Delta-method Std. error**
INTERCEPT **	-49.79526	16.3262	—	—	—	—
$\widehat{SYCV}$ **	0.0882208	0.0341718	0.0107282	0.00426	0.0089146	0.0038042
COLLEGE **	0.5319554	0.1775544	0.080691	0.03045	0.0715585	0.0265996
AGE **	0.0224546	0.0083496	0.0027055	0.00121	0.0022371	0.0011191
YIELDS	0.0000573	0.0004202	-6.13e-06	0.00004	-0.0000108	0.000038
SOIL QUALITY	0.08912	0.2702543	0.0105953	0.0177	0.0086978	0.0141989
IMPORTANCE	0.4505202	0.3765342	0.0433693	0.04656	0.029047	0.049415
PROFIT **	0.7177929	0.2379991	0.1259076	0.03178	0.1230152	0.0289001
INCOME **	0.0101478	0.0033864	0.0014051	0.00051	0.0012427	0.0004661
COMPUTER ***	0.9543703	0.2060244	0.1245066	0.02965	0.1108462	0.0284585
MANURE	0.1562928	0.2521209	0.0239106	0.03733	0.0212166	0.0326289
AL	-0.2337655	0.8014688	-0.0265886	0.0901	-0.0220207	0.0913249
AR	0.1271238	1.736523	0.0248937	0.13206	0.0236474	0.1122524
FL	-0.4013635	1.622539	-0.028784	0.11512	0.0022819	0.1207144
GA	0.5574693	0.7213172	0.1089773	0.11793	0.0918848	0.0851728
LA	1.014414	0.7678541	0.1220569	0.14269	0.0968283	0.0990682
MS	0.5406264	0.7546535	0.0751883	0.11771	0.0595753	0.0897305
MO	0.057978	1.827293	-0.0020292	0.12082	-0.0045794	0.1129373
NC	0.0885384	0.7624302	0.0098212	0.09242	0.0077217	0.0835799
SC	0.6903778	0.8796235	0.0534864	0.12135	0.0465352	0.097552
TN	-0.0104167	0.7940089	0.0061853	0.09897	0.0089126	0.0894238
TX **	-2.165139	0.8362593	-0.2517155	0.07769	-0.2404691	0.0885687
VA	(omitted)	—	—	—	—	—

[1]No. of Obs. 918 Wald χ^2 (38) = 265.50 Log likelihood = -776.77199 Pseudo R^2= 0.1509 Prob> χ^2= 0.0000