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Bundled Adoption of Precision Agriculture Technologies by Cotton Producers

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This research analyzes the adoption patterns among cotton farmers for remote sensing, yield monitors, soil testing, soil electrical conductivity, and other precision agriculture technologies using a Multiple Indicator Multiple Causation regression model. Adoption patterns are analyzed using principle component analysis to determine natural technology groupings. Identified bundles are regressed on farm structure and operator characteristics. The propensity to adopt technology bundles was greater for producers managing relatively larger operations who used a variety of information sources to learn about precision farming, irrigated cotton, practiced crop rotation, and participated in working land conservation programs.

Key words: adoption, cotton, Multiple Indicator Multiple Causation model, precision agriculture, technology bundles

Introduction

Despite the anticipated gains in input use efficiency and increased profit margins typically associated with knowledge about soil fertility, field topography, and other field characteristics, adoption of some precision agriculture information technologies remains relatively low in cotton production. Mooney et al. (2010) found that less than 1% of cotton producers used digital maps to aid input use decisions, and 4% used soil electrical conductivity devices. A national survey conducted by the United States Department of Agriculture Economic Research Service found that GPS devices were used to develop soil maps on 5.2% of the planted cotton area in 2007 (United States Department of Agriculture, Economic Research Service, 2007).

Use of soil survey maps has a long history, and grid and zone soil testing is considered an entry technology into precision agriculture (Schimmelpfennig and Ebel, 2011). Yield monitors are also considered an entry-level technology into precision agriculture given farmers' intense interest in yields on their farms (Lowenberg-DeBoer, 1999). However, the rate of yield monitor adoption by cotton farmers lagged behind the adoption of yield monitoring by grain farmers because of early problems in developing reliable monitors for cotton (Larson et al., 2005). Yet according to surveys of upland cotton producers, the adoption of yield monitors with GPS in cotton production has risen from 2.8% in 2001 to 19% in 2013 (Larson et al., 2005; Boyer et al., 2014). One factor influencing adoption of cotton yield monitors may be the 2007 introduction of on-board module builders on cotton harvesters that are paired with yield monitoring technology (Reuters, 2008). Farmers may find value in combining the two technologies because of reduced equipment and

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labor expenses associated with the elimination of boll buggies and module builders in the harvest equipment complement (Martin and Varco, 2008).

Surveys of upland cotton producers provide further insight into how bundling technologies may be an important factor influencing adoption of precision agriculture technologies by cotton farmers. In a 2009 survey of upland cotton producers, Walton et al. (2010b) found that 21% of producers used soil survey maps and that 22% and 11% of cotton producers used grid and zone soil sampling, respectively. In 2010, about 7% of cotton producers surveyed in the southern states used handheld GPS devices (Mooney et al., 2010). Decision support software such as COTMAN (Computerized Cotton Management System) can be used to digitally document and record plant growth (i.e., plant mapping) using handheld GPS devices (Bange et al., 2004). About 5% of cotton growers surveyed by Mooney et al. (2010) used COTMAN. Using data from a 2005 survey of upland cotton producers, Walton et al. (2010a) found that farmers who used COTMAN, remote sensing (e.g., aerial and satellite imagery), and grid soil sampling were more likely to have used handheld GPS devices. Pandit et al. (2011) indicated that of 1,800 cotton farmers surveyed in thirteen U.S. states, ninety-nine had adopted two precision farming technologies, fifty-five had adopted three precision farming technologies, twenty-four had adopted four precision farming technologies, and nine had adopted five precision farming technologies. The aforementioned studies by Walton et al. (2010a) and Pandit et al. (2011) support the idea that farmers tend to adopt precision technologies in bundles.

Marketing of information technology and analytic services by the agricultural support industry continues to increase, but adoption of technologies such as remote sensing, soil electrical conductivity, or digital maps by cotton producers remains comparatively low. Precision farming technologies are attribute technologies (Tenkorang and Lowenberg-DeBoer, 2008). That is, the information generated by one technology ideally complements data recorded by other technologies. In their study of retail precision agriculture dealerships, Holland, Erickson, and Widmar (2013) found that yield monitoring services were provided by 23% of the businesses surveyed. The same survey reported that 33% of precision agriculture dealerships provided satellite/aerial imagery services. Soil sampling with GPS was provided by 57% of the dealerships, with grid and zone soil sampling services following closely at 54% and 35% of businesses, respectively. Bundling technologies may reduce costs for some businesses because it is less expensive to sell several goods in a single package (Varian, 1999). In other words, bundling allows firms to charge customers different prices for items they would not necessarily purchase if sold alone (Perloff, 2007).

This study analyzes the adoption of information and processing technologies associated with precision agriculture based on a 2013 survey of cotton producers in thirteen southern states. The research focus is on the bundling of these technologies as evidenced by their adoption. We estimate a Multiple Indicator Multiple Causation (MIMIC) model to generate adoption propensity scores. These scores are subsequently analyzed using principle component analysis (PCA) to identify bundles of technologies based on their use by producers. The bundles identified with PCA are subsequently regressed on farm structure and operator characteristics to isolate which factors are associated with specific technology bundle adoption, holding other variables constant. Ten discrete technologies are considered in the analysis: yield monitors, grid soil sampling, zone soil sampling, soil electrical conductivity, digital map use, aerial imagery, satellite imagery, soil survey maps, handheld GPS devices, and the decision aid COTMAN. Identifying natural bundles of technologies could be useful for agricultural service providers and industry professionals to lower marketing costs and increase revenue by selling bundled products. From the perspective of producers, understanding the synergy potential among advanced information technologies can lower variable input costs and leverage on-farm scale economies.

Conceptual Model

Producers maximize returns from cotton production less variable costs by choosing optimal input combinations including fuel, fertilizer, labor, and land. Input quantity decisions are a function of the relative price of cotton with respect to factor market prices and land rental costs as well as unobserved characteristics such as experience and ability. Cotton producers make decisions about input use and land allocated to cotton production, but the effects of weather and random outbreaks of weed and pest infestations on plant growth are typically beyond the producer's control.

Producers reduce production uncertainty by generating field-specific information about the spatial distribution of soil fertility with precision agriculture technologies including aerial imagery, electrical conductivity, grid and zone soil sampling, GPS, and other data-generating activities such as map-making. Site-specific data collected at different spatial and temporal resolutions may be stored or analyzed using a variety of instruments, software, or technologies. A producer adopts one or a combination of technologies when the additional net revenue along with possibly nonmarket benefits (I) from adopting k technologies exceeds the cost of adopting the technology or technologies. With k technology options available, there are $M = 2^k - 1$ potential technology sets the researcher could observe in the population of adopters, counting sets that include adoption of only one technology.

In this analysis there are ten technologies considered with $k =$ cotton yield monitors (CYM), grid soil sampling (GSS), zone soil sampling (ZSS), aerial imagery (AIM), satellite imagery (SIM), soil survey maps (SSM), handheld GPS devices (HGG), COTMAN (CTM), electrical conductivity devices (ECM), and digital elevation maps (DGM), which correspond to $M = 1,023$ potential bundles. The mth technology set is adopted when $V(m, I_m; X) > \cup_n^{M-1} V(n, I_n; X)$, where n indexes technology bundles other than set m, V is an indirect utility function, I is income, $\cup$ the union operator, and X are variables specific to a producer and farm operation. The utility enjoyed by the producer (V^*, a latent variable) when $V(m, I_m; X) - \cup_n^{M-1} V(n, I_n; X) > 0$ is unobserved by the researcher. This interpretation of latent utility differs from conventional applications. In other words, V^* represents the propensity to adopt precision agriculture technologies rather than the likelihood of adopting any single technology. In the latter case, utility is typically modeled as a discrete 0/1 choice, such that $V_k = 1$ if $V_k^* > 0$, 0 otherwise. We use this relationship between the adoption of individual technologies and the more general idea of adoption propensity to motivate the empirical model as a Multiple Indicator Multiple Causation (MIMIC) regression.

Empirical Model

The combinatorial aspect of this discrete decision-making problem typically demands analysis using multinomial logit or multivariate probit regression presented as some permutation of McFadden's (1974) random utility model. For example, when multiple technologies are considered, most technology adoption analyses model discrete adoption decisions as linear functions of exogenous covariates (typically operator characteristics or farm structure variables) and a stochastic error component (ε); for example, for the kth technology $V_k^* = X\beta_k + \varepsilon_k$. In this case, producer and farm-specific covariates are hypothesized to influence the adoption of technology k differently.

This analysis takes a different approach to analyzing the adoption of multiple precision agriculture technologies. Instead, the focus is on the propensity of producers to adopt precision agriculture technologies generally, recognizing that adoption of individual technologies may be correlated. A MIMIC model is applied to this effect.

Early applications of MIMIC models are found in Zellner (1970) and Joreskog and Goldberger (1975). Maddala (1983) was an early application of the MIMIC model to agricultural technology adoption. Richards and Jeffrey (2000) also applied a MIMIC model to analyze efficiency and economic performance of the Canadian dairy sector. We apply these adoption models, extending Skrondal and Rabe-Heskath's (2004) generalization of MIMIC models to the broad class of multi-factor latent variable models. Their generalization accommodates the simultaneous modeling of discrete variables in a general linear model framework.

The propensity of the ith cotton producer to adopt precision agriculture technologies is an unobserved latent-index variable that is linear in terms:

$$Z_i^* = \boldsymbol{X}_i\boldsymbol{\Gamma} + u_i. \tag{1}$$

The propensity to adopt any technology (Z^*) is a function of farm structure, operator characteristics, and variables external to the farm (X) hypothesized to influence the likelihood of adopting one or a combination of technologies, and an unobserved random component u_i, with $Var(u_i) = \tau$.

Adoption of the kth technology is also a latent variable and linear in arguments:

$$CYM_i^* = \alpha_1 + \lambda_1 Z_i^* + \varepsilon_{CYM,i}, \qquad CYM_i = \begin{cases} 1, & CYM_i^* > 0 \\ 0, & CYM_i^* \le 0 \end{cases} \tag{2a}$$

$$GSS_i^* = \alpha_2 + \lambda_2 Z_i^* + \varepsilon_{GSS,i}, \qquad GSS_i = \begin{cases} 1, & GSS_i^* > 0 \\ 0, & GSS_i^* \le 0 \end{cases} \tag{2b}$$

$$ZSS_i^* = \alpha_3 + \lambda_3 Z_i^* + \varepsilon_{ZSS,i}, \qquad ZSS_i = \begin{cases} 1, & ZSS_i^* > 0 \\ 0, & ZSS_i^* \le 0 \end{cases} \tag{2c}$$

$$AIM_i^* = \alpha_4 + \lambda_4 Z_i^* + \varepsilon_{AIM,i}, \qquad AIM_i = \begin{cases} 1, & AIM_i^* > 0 \\ 0, & AIM_i^* \le 0 \end{cases} \tag{2d}$$

$$SIM_i^* = \alpha_5 + \lambda_5 Z_i^* + \varepsilon_{SIM,i}, \qquad SIM_i = \begin{cases} 1, & SIM_i^* > 0 \\ 0, & SIM_i^* \le 0 \end{cases} \tag{2e}$$

$$SSM_i^* = \alpha_6 + \lambda_6 Z_i^* + \varepsilon_{SSM,i}, \qquad SSM_i = \begin{cases} 1, & SSM_i^* > 0 \\ 0, & SSM_i^* \le 0 \end{cases} \tag{2f}$$

$$HGG_i^* = \alpha_7 + \lambda_7 Z_i^* + \varepsilon_{HGG,i}, \qquad HGG_i = \begin{cases} 1, & HGG_i^* > 0 \\ 0, & HGG_i^* \le 0 \end{cases} \tag{2g}$$

$$CTM_i^* = \alpha_8 + \lambda_8 Z_i^* + \varepsilon_{CTM,i}, \qquad CTM_i = \begin{cases} 1, & CTM_i^* > 0 \\ 0, & CTM_i^* \le 0 \end{cases} \tag{2h}$$

$$ECM_i^* = \alpha_9 + \lambda_9 Z_i^* + \varepsilon_{ECM,i}, \qquad ECM_i = \begin{cases} 1, & ECM_i^* > 0 \\ 0, & ECM_i^* \le 0 \end{cases} \tag{2i}$$

$$DGM_i^* = \alpha_{10} + \lambda_{10} Z_i^* + \varepsilon_{DGM,i}, \qquad DGM_i = \begin{cases} 1, & DGM_i^* > 0 \\ 0, & DGM_i^* \le 0 \end{cases} \tag{2j}$$

where α_k is a constant specific to each technology adoption equation, $Var(\varepsilon_k) = \theta_k$, and λ_k is a factor loading (Skrondal and Rabe-Hesketh, 2004) correlating the propensity to adopt precision agriculture technologies with the kth technology. Significant factor loadings suggest the indicator variables (e.g., the discrete use of each technology) are good indicators of the propensity to adopt precision agriculture technology (Maddala and Trost, 1981). Figure 1 summarizes the equation system and the hypothesized links among farm and operator characteristics, the latent adoption variable, and the technologies considered. The covariates (X) included in the linear adoption propensity equation (equation 1) are discussed in sequel, with variable descriptions and their summary statistics reported in table 1.

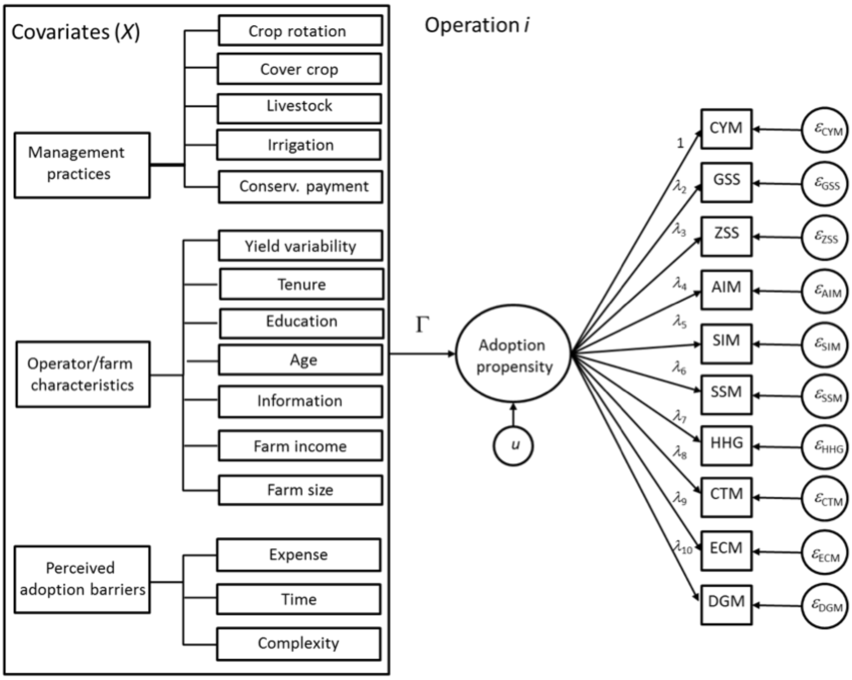

Figure 1. Multiple Indicator Multiple Causation Design for Analyzing Adoption of Precision Agriculture Technology Bundles

Operator and Farm Characteristics

Farm operator age is typically negatively associated with technology adoption (Daberkow and McBride, 2003). Older farmers may be less willing to face learning curves or may have a shorter planning horizon than younger farmers (Roberts et al., 2004). We expect that respondent age will be negatively associated with the propensity to adopt precision agriculture technologies.

Education is typically hypothesized to be positively correlated with the propensity to adopt precision agriculture technologies (Walton et al., 2008). Farmers with higher levels of education may be better equipped to adopt more complex information technologies requiring the management and coordination of large volumes of information. We include an ordinal variable (scale, 1–6), with 1 indicating that the producer attended (but did not complete) high school and 6 indicating that the respondent has a college degree.

Cotton producers access a variety of information sources to learn about the types and quality of various precision agriculture technologies available to them or to update their skills in using precision agriculture technologies (Jenkins et al., 2011). We hypothesize that the number of information sources used by a producer will be positively associated with the propensity to adopt a variety of precision agriculture technologies.

Operation size was measured by the number of cotton acres planted. Farm size was hypothesized to be positively associated with the propensity to adopt precision agriculture technologies. The costs associated with these technologies are lower when spread over more acres.

Producers earning relatively more of their income from the farm operation may be more likely to invest in technologies that are expected to increase efficiency. The percentage of household income from farming was included in the linear index model to control for this effect.

The ratio of total owned cotton acres farmed to acres rented to produce cotton was hypothesized to be positively correlated with the propensity to adopt precision agriculture technologies. Producers

Table 1. Summary Statistics of Adopted Technologies and Covariates

Variable	N	Mean	Std. Dev.	Min	Max
Operator education (ordinal, 1–6)	1,780	3[a]		1	6
Operator age (years)	1,783	55.49	13.40	18	98
Number of information sources used (count)	1,814	1.99	1.46	0	8
Cotton acres farmed (acres)	1,812	493.96	771.61	0	10,000
% income from farming	1,607	73.48	28.34	0	100
Owned/operated cotton area (ratio)	1,203	39.09	38.19	0	100
Livestock (= 1)	1,758	0.29		0	1
Irrigation (= 1)	1,814	0.27		0	1
Crop rotation area (%)	1,814	53.02	38.75	0	100
Cover crop area (%)	1,814	20.73	35.08	0	100
Conservation payment (= 1)	1,615	0.12		0	1
Yield variability (index)	1,300	57.29	925.02	0	33,320.48
Barrier: expensive (= 1)	1,814	0.44		0	1
Barrier: time consuming (= 1)	1,814	0.02		0	1
Barrier: complexity(= 1)	1,814	0.08		0	1
Delta region (= 1)	1,814	0.13		0	1
Corn Belt region (= 1)	1,814	0.04		0	1
Appalachian region (= 1)	1,814	0.23		0	1
Southeast region (= 1)	1,814	0.25		0	1
Used cotton yield monitor (= 1)	1,814	0.19		0	1
Practiced grid soil sample (= 1)	1,814	0.22		0	1
Practiced zone soil sample (= 1)	1,814	0.12		0	1
Used aerial images (= 1)	1,814	0.11		0	1
Used satellite imagery (= 1)	1,814	0.06		0	1
Used soil survey maps (= 1)	1,814	0.13		0	1
Used handheld GPS devices (= 1)	1,814	0.08		0	1
Used COTMAN (= 1)	1,814	0.02		0	1
Used electrical conductivity devices (= 1)	1,814	0.05		0	1
Used digital maps (= 1)	1,814	0.02		0	1

Notes: [a] Median value of variable.

farming relatively more of the land they own may be more likely to expend more managerial attention to their owned land than land farmed under rental agreements (Roberts et al., 2004).

Managing inputs more effectively may decrease yield variability (Larson and Roberts, 2004). Yield variability may reflect within-field soil fertility variation. This variable was hypothesized to be positively correlated with the propensity to adopt precision agriculture technologies.

Management Practices

Management of other farm activities not directly related to cotton production may reduce the time available to effectively apply soil test information. The effect of enterprise diversification on the propensity to adopt precision agriculture technologies was measured by livestock ownership. This variable was expected to be negatively correlated with adoption propensity.

Interactions between fertilizer use and irrigation affect yield (Roberts et al., 2006). Input requirements for cotton production are higher for irrigated crops (Larson et al., 2008). Cotton producers may be more inclined to use precision farming technologies to optimize the placement of fertilizer on irrigated cotton acres.

Cotton producers using best management practices (BMPs) such as cover crops and crop rotation may be more likely to adopt one or a combination of precision farming technologies. These BMPs improve soil structure, conserve water, enhance soil fertility, and control weed and pest infestations. The skill and ability needed to coordinate the establishment and management of cover crops and rotating cotton with other crops may be indicative of a more general sense of farm planning and the proclivity to adopt precision farming technologies. The percentage of cotton acres planted with cover crops and the percentage of cotton acres rotated with other crops are included as farm managerial covariates.

The USDA Natural Resources Conservation Service provides cost-share opportunities to row crop producers to develop soil nutrient management plans through programs such as the Environmental Quality Incentive Program and the Conservation Stewardship Program (United States Department of Agriculture, National Resources Conservation Services, 2011). It is hypothesized that cotton producers who participate in these programs and receive cost-share payments to develop and implement soil nutrient management plans will exhibit a higher propensity to adopt the precision agriculture technologies examined here.

Perceived Barriers to Adoption

The perceived monetary and time opportunity costs that cotton producers associate with precision agriculture technologies are likely barriers to their adoption. Producers may also believe that managing multiple sources of data generated by various devices may generate confounding information and complicate management.

Binary 0/1 variables indicating whether a respondent believed that monetary expense, time, or instrument complexity were barriers impeding their adoption of precision agriculture technologies were included in the adoption propensity equation. The expected relationships are negative.

Farm Production Regions

Regional trends in growing degree days, weather, and topography may influence the propensity to adopt specific precision agriculture technologies. Five regions were identified across the fourteen states: the Mississippi Delta region (including Louisiana, Arkansas, and Mississippi), the Corn Belt/grain-producing region (including Missouri and Kansas), the mid-southern region (including Tennessee, North Carolina, and Virginia), the southern plains region (Texas and Oklahoma), and the southeastern states (South Carolina, Georgia, Alabama, and Florida). The regional dummy variables were orthogonally restricted such that the coefficients are interpreted as differences from the population mean instead of a specific reference group (Neter et al., 1996).

Survey Data

The empirical analysis uses data from a 2013 survey of cotton producers in Alabama, Arkansas, Florida, Georgia, Kansas, Louisiana, Mississippi, Missouri, North Carolina, Oklahoma, South Carolina, Tennessee, Texas, and Virginia (Boyer et al., 2014). The Cotton Board (Memphis, Tennessee) provided a list frame of cotton producers who marketed cotton in 2011. After removing university research and education centers and duplicate names, the mailing list comprised 13,566 cotton producers.

Survey implementation followed Dillman's (2001) tailored design survey method. A postcard was sent to inform cotton producers about the survey. A week later, surveys were mailed with a postage-paid return envelope and a cover letter explaining the purpose of the survey. A reminder postcard was mailed one week later. The second survey wave followed one week later, mailed to individuals who had not responded to the first survey. Individuals who had not produced cotton between 2008 and 2012 were instructed to return the survey unanswered. The response rate was 13.76%. For the regression analysis, there were 739 observations after eliminating records with missing observations.

Post-stratification weights (expansion factors) were formulated using the method developed by (Lambert et al., 2014). The expansion factors were estimated based on the total cotton acres in each of the states represented in the survey. These weights were used to estimate total cotton acres managed under each information technology.

Estimation Methods

The equation system is estimated as a general linear model with a logistic link function (Skrondal and Rabe-Hesketh, 2004). Identification of the system relies on the following restrictions. The first restriction requires an arbitrary normalization of either the variance term of equation (1) or one of the factor loadings of equations (2a)–(2j) (Maddala, 1983). We restrict variance $\tau = 1$. Second, the variance terms of equations (2a)–(2j) are constant and identical (i.e., $\theta_k = \pi^2/3$) because the adoption of each technology is observed as a 0/1 binary variable. Third, the off-diagonals of the error covariance of each technology adoption equation and the adoption propensity equation are 0. Lastly, the covariance matrix between equations (2a)–(2j) is null.

The last restriction provides some intuition to the MIMIC model. Correlation between technology adoption decisions is modeled through the factor loadings (the λ_ks) and a single latent variable indexing the propensity to adopt precision agriculture technologies in general. It is important to note that the last assumption restricts the covariates used to explain the propensity to adopt precision agriculture technologies to be identical among the technologies. The difference in the magnitude a covariate has on the adoption of each technology considered separately is determined by the factor loadings corresponding with the latent variable in each technology adoption equation.

The null model is that the loading factors of equations (2a)–(2j) and the respective coefficients included in the adoption index (equation 1) are jointly not different from 0. This hypothesis is tested using a likelihood ratio test with 28 degrees of freedom (10 factor loadings plus 18 covariates included in equation 1).

Using the logistic distribution to examine the correlation between the propensity to adopt precision farming technologies and each technology considered has practical advantages in terms of interpreting model results. For example, expressing equations (2a)–(2j) in log-odds form for technology k:

$$(3) \qquad \ln\left(\frac{P^*_{ik}}{1-P^*_{ik}}\right) = \hat{\alpha}_k + \hat{\lambda}_k Z^*_i,$$

where P^*_{ik} is the probability of adopting technology k and $\hat{}$ denotes estimates. From the standard expression for log-odds proportions, $exp(\hat{\lambda}_k \cdot \hat{\gamma}_h)$, where $\hat{\gamma}_h$ is an element of $\mathbf{\Gamma}$ in equation (1), the percentage change the hth covariate has on the odds of adopting technology k is calculated as $100 \times [exp(\hat{\lambda}_k \cdot \hat{\gamma}_h) - 1]$ (Long and Freese, 2006).

An *ex post* principal component analysis (PCA) of the predicted adoption patterns was conducted to identify conditional technology bundles. First, the adoption probabilities of each technology, given the propensity to adopt precision agriculture technologies in general, were estimated. In the second stage, technology clusters were determined using PCA. Lastly, the first and second components were plotted to graphically inspect natural groupings. Using logistic regression, identified bundles were regressed on farm and farmer characteristics to examine the factors correlated with bundle adoption.

Results

The weighted sum of the 2012 cotton acres farmed in the survey region was 8,770,793 acres, which corresponds with 17,610 cotton acres managed by $n = 1,812$ respondents (table 2). Discussion of acres managed under the precision agriculture technologies analyzed focuses on the weighted aggregation, but the use patterns are nonetheless similar in terms of weighted and unweighted

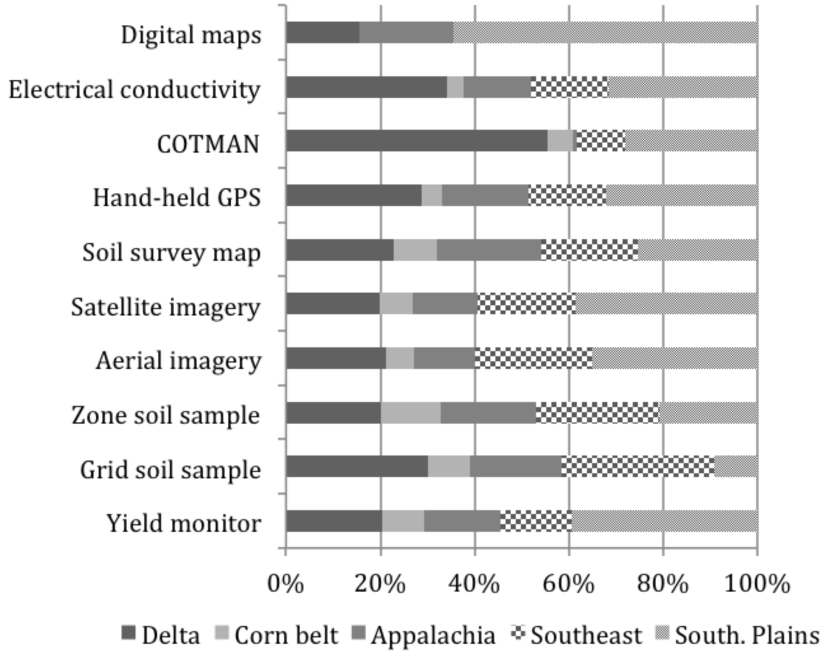

Figure 2. Distribution of 2012 Cotton Acres Managed under Each Technology

Notes: Base acres managed under each technology are reported in table 1.

Table 2. Farms Adopting and Cotton Acres Managed with Precision Agriculture Technologies

Technology	Survey	(%)	Expanded Farms	(%)	Expanded Acres	(%)
Yield monitor	225	(19)	2,650	(15)	1,936,231	(22)
Grid soil sample	266	(22)	3,128	(18)	1,955,288	(22)
Zone soil sample	152	(13)	1,654	(9)	1,095,176	(12)
Aerial imagery	141	(12)	1,875	(11)	1,104,996	(13)
Satellite imagery	71	(6)	936	(5)	594,558	(7)
Soil survey map	159	(13)	1,921	(11)	1,060,839	(12)
Handheld GPS	89	(7)	1,056	(6)	713,846	(8)
COTMAN	22	(2)	305	(2)	303,716	(3)
Electrical conductivity	56	(5)	670	(4)	496,878	(6)
Digital maps	27	(2)	336	(2)	251,000	(3)
Total	1,812		17,610		8,770,793	

acreage rankings. Yield monitors with GPS and grid soil sampling were used on 22% of the cotton acres farmed in 2012. The cotton acres managed using zone soil sampling, aerial imagery, and soil survey maps were similar, between 12% and 13% of the total cotton acres. Handheld GPS devices, satellite imagery, and electrical conductivity technologies were used on 8%, 7%, and 6% of cotton acres in 2012. The decision-making software COTMAN and digital maps were used to make managerial decisions on 3% of the 2012 cotton crop.

Relatively more cotton acres were managed using GPS-equipped yield monitors in the southern plains region (39%) (figure 2). Cotton acres managed in the corn production region were less intensively managed using yield monitors. Table 2 summarizes the pattern of technology bundles adopted by cotton producers in 2012. About 64% of the 2012 cotton acres managed with grid soil

Table 3. Distribution of Precision Agriculture Technology Adoption among Cotton Producers, 2013

CYM	GSS	ZSS	AIM	SIM	SSM	HHG	CTM	ECM	DIM	Survey	Expanded	Cumulative
*										79	806	12.93%
	*									91	780	25.45%
*	*									53	366	31.33%
		*								32	285	35.90%
	*				*					20	238	39.72%
	*		*							14	158	42.25%
			*		*					11	133	44.39%
	*	*								14	131	46.50%
					*					11	115	48.35%
	*					*				10	111	50.13%
	*		*		*					11	107	51.86%
		*			*					9	101	53.48%
*			*							6	84	54.83%
	*			*						4	68	55.92%
*	*			*						1	63	56.94%
			*			*				5	62	57.94%
			*	*	*					6	61	58.92%
*						*				5	57	59.83%
						*				10	55	60.72%
			*	*						4	54	61.59%
*	*		*							4	51	62.41%
*	*	*			*					9	50	63.22%
*		*								11	50	64.01%
			*							8	49	64.80%
		*	*							4	47	65.56%
*			*		*					6	46	66.30%
	*	*						*		3	42	66.98%
			*	*					*	2	40	67.63%
								*		2	40	68.27%
			*	*	*		*			1	39	68.89%
	*		*	*	*					3	38	69.50%
*		*			*					7	37	70.09%
*	*				*					11	36	70.67%
*	*				*			*		2	36	71.25%
*		*				*		*		2	35	71.81%
*									*	2	34	72.36%
		*	*		*					6	34	72.90%
	*		*	*						3	34	73.45%
*	*				*	*				3	34	73.99%
*	*		*	*	*					4	34	74.53%
*	*	*	*	*	*	*				5	32	75.04%
*	*	*	*	*	*	*	*	*	*	2	31	75.53%
			*	*	*			*		2	30	76.02%
*	*							*		6	30	76.50%
				*						3	29	76.97%
		*						*		4	29	77.44%
*	*	*	*							4	28	77.90%
		*	*		*					2	28	78.35%
		*					*			2	27	78.79%
*		*			*	*				2	26	79.21%
							*			2	25	79.60%
*			*		*	*				1	24	80.00%
	*		*			*				2	24	80.39%
*		*						*		6	24	80.78%
	*	*			*					3	24	81.15%
					*			*		1	23	81.52%

Continued on next page...

Table 3. – continued from previous page

CYM	GSS	ZSS	AIM	SIM	SSM	HHG	CTM	ECM	DIM	Survey	Expanded	Cumulative
	*							*		1	23	81.89%
			*		*			*		1	23	82.25%
*			*			*				2	23	82.62%
		*	*	*			*			1	23	82.99%
*	*	*		*	*	*		*		1	23	83.35%
	*				*	*	*			1	23	83.72%
*	*	*						*		6	22	84.08%
		*	*			*				2	20	84.41%
		*	*		*				*	1	20	84.73%
*	*		*			*				2	20	85.06%
*	*	*					*	*		2	20	85.39%
		*		*						2	20	85.71%
	*		*		*	*	*			1	20	86.03%
*			*		*	*	*			1	20	86.35%
		*	*	*	*	*				2	20	86.67%
	*	*			*	*		*		2	20	86.99%
			*	*		*				4	20	87.30%
		*	*					*		1	19	87.61%
*		*	*	*	*	*		*		1	19	87.92%
*										2	18	88.21%
	*								*	2	18	88.50%
*			*	*		*				1	18	88.78%
*	*	*		*	*			*	*	1	18	89.07%
*	*	*			*	*				3	18	89.35%
				*				*		1	17	89.63%
*					*					6	17	89.90%

Notes: CYM = cotton yield monitor; GSS = grid soil sampling; ZSS = zone soil sampling; AIM = aerial imagery; SIM = satellite imagery; SSM = survey soil map; HHG = handheld GPS; CTM = COTMAN; ECM = electrical conductivity map; DIM = digital elevation map. Cumulative percentages based on expanded cotton farm population.

sampling information were located in the Delta and southeastern states. Cotton acres managed using zone soil sampling information were more uniformly distributed across the survey region. The distribution of cotton acres managed using satellite or aerial imagery were concentrated in the southeastern and southern plains states, with a majority of these acres located in Texas and Oklahoma (35% and 39% for aerial and satellite imagery). Most (64%) of the cotton acres managed using data generated from digital maps were also located in these states. Cotton acres managed by producers using the software support system COTMAN were concentrated in Mississippi, Arkansas, and Louisiana (55%), while cotton acres managed using data generated by electrical conductivity devices were mostly located in the Delta states, Texas, and Oklahoma (combined, 66% of all cotton acres managed under this technology). The use of soil maps to make managerial decisions for cotton production was uniformly distributed across the regions, excluding Kansas and Missouri; only 9% of the total acres managed using soil survey maps were located in these states. A majority of the 2012 cotton acres managed using handheld GPS devices were located in Texas and Oklahoma (39%) followed closely by Louisiana, Mississippi, and Arkansas (29%).

There were 154 technology combinations used by cotton producers in the survey region. The predominant, unconditional technology combinations adopted by 90% of cotton growers are reported in table 3. Of the top eighty-four technology sets, the most common combination was GPS-equipped yield monitors and grid soil sampling (53 respondents, with a corresponding expanded population of 366 cotton farms). Common technology combinations tended to exclude the use of digital elevation maps, electrical conductivity devices, and COTMAN. Combinations that included these technologies begin appearing at the sixty-seventh percentile of the distribution of cotton growers. Adoption of all ten technologies considered was a rare event ($n = 2$ respondents), but adoption of single technologies—such as yield monitors, grid soil sampling, or zone soil sampling—was relatively common.

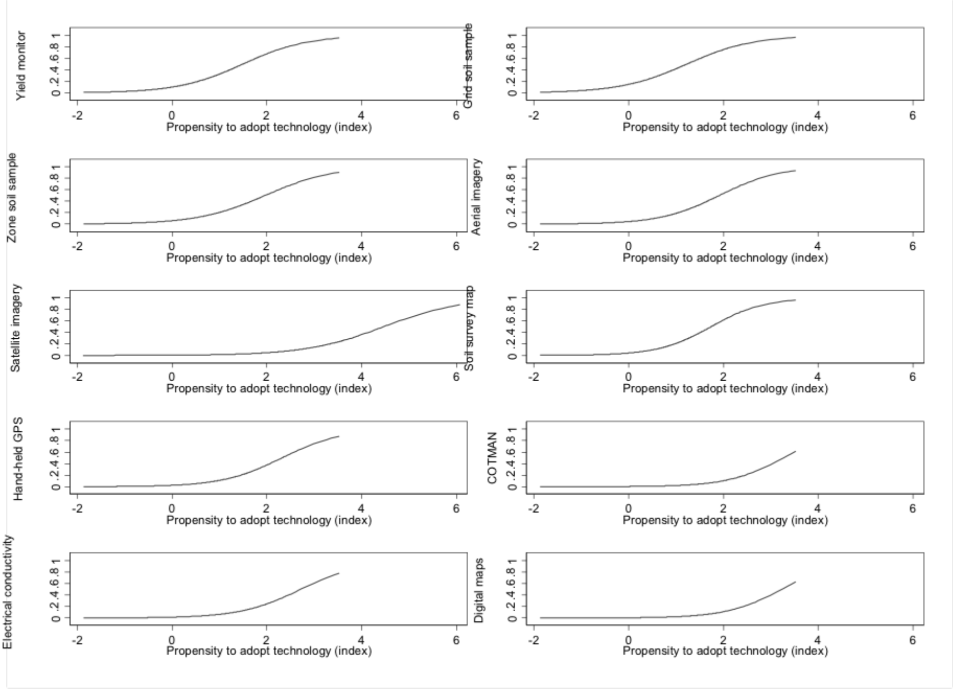

Figure 3. Adoption Curves and the Propensity to Adopt Precision Agriculture Technologies among Cotton Producers

MIMIC Regression Results

The likelihood ratio statistic was $-2[-2{,}610-(-2{,}067)] = 1{,}086(\mathrm{df}=28)$, which suggests that the unrestricted model is preferred to the null model at $P < 0.0001$ (table 4). The factor-loading scores were significant at the 1% level, suggesting that these technologies are strong indicators of the latent variable "propensity to adopt precision agriculture technologies." The factor loading on the propensity to adopt precision agriculture technologies was largest for soil survey maps, followed by use of satellite imagery. The weakest (but significant) factor loading association was observed with zone soil sampling. These patterns are evidenced by the adoption curves of each technology over the distribution of adoption propensity scores (figure 3). Discussion of the covariates explaining the propensity to adopt these technologies follows table 5, which calculates the percentage changes in the log odds associated with each technology adopted.

Operator age was negatively associated with the propensity to adopt these technologies, a finding commensurate with previous literature and technology adoption (table 5). The association was strongest with soil survey map technology: an additional year in age was associated with a $100 \times [exp(-0.0218 \times 1.804) - 1] = -3.86\%$ decrease in the odds of using satellite imagery to make input management decisions. Averaging across the percentage changes in log odds across all technologies, an additional year in age was associated with a 3.45% decrease in the odds of adopting any of the ten technologies considered.

Cotton growers using relatively more information sources to update their knowledge about precision farming were more likely to adopt the technologies examined. The association between adoption propensity and the number of information sources used was strongest for the use of soil survey maps. For example, a one-unit increase in the number of information sources used was associated with a 30.60% increase in the odds that a cotton producer used soil survey maps to make input management decisions. On average, use of an additional source of information was associated with a 26.95% increase in the odds of using soil survey maps.

Table 4. Multiple Indicator Multiple Causation Model (MIMIC) Estimates

	Coefficients	
Technology	**Factor Loading Estimate (λ_k)**	**Constant (α_k)**
Yield monitor	1.4787***	−2.2026***
Grid soil sample	1.4327***	−1.7588***
Zone soil sample	1.4076***	−2.7706***
Aerial imagery	1.6013***	−3.0724***
Satellite imagery	1.8033***	−4.4086***
Soil survey map	1.8041***	−3.1436***
Handheld GPS	1.5921***	−3.6904***
COTMAN	1.7170***	−5.5983***
Electrical conductivity	1.5678***	−4.2682***
Digital maps	1.7045***	−5.5143***
Adoption propensity component (Z^*)	**Estimate (Γ)**	
Operator education (ordinal, 1–6)	0.0589	
Operator age (years)	−0.0218***	
Number of information sources used (count)	0.1480***	
Cotton acres farmed (acres)	0.0003***	
% income from farming	0.0051**	
Owned/operated cotton area (ratio)	−0.0021	
Livestock (= 1)	−0.0265	
Irrigation (= 1)	0.3152**	
Crop rotation area (%)	0.0042***	
Cover crop area (%)	0.0018	
Conservation payment (= 1)	0.6812***	
Yield variability (index)	−0.0001	
Barrier: expensive (= 1)	−0.1199	
Barrier: time consuming (= 1)	−0.1640	
Barrier: complexity(= 1)	−0.2208	
Delta region	0.5838***	
Corn Belt region	0.0774	
Mid-southern region	0.1370	
Southeast region	−0.2077**	
τ (restricted)	1.0000	
N	739	
Restricted pseudo log likelihood	−2,610	
Unrestricted pseudo log likelihood	−2,068	
McFadden's pseudo R^2	0.21	

Notes: Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level.

Farm size was positively correlated with the latent adoption variable, a finding consistent with most agricultural technology adoption studies. The relationship was strongest with the use of soil survey maps and the use of satellite imagery. Given a 100-acre change in the area managed by a cotton producer, the odds of using soil survey maps or satellite imagery increased by 5.41%. Averaging across the percentage changes for farm size in table 5, a 100-acre increase in the cotton acres managed was associated with a 4.83% change in the odds of using one of the technologies.

The percentage of income from farming was positively associated with the propensity to

Table 5. Percentage Changes in Adoption Odds

Covariate	Yield Monitor	Grid Soil Sample	Zone Soil Sample	Aerial Imagery	Satellite Imagery	Soil Survey Map	Handheld GPS	COTMAN	Electrical Conductivity	Digital Maps
Operator age (years)	−3.17	−3.08	−3.02	−3.43	−3.85	−3.86	−3.41	−3.67	−3.36	−3.65
Information sources used (count)	24.46	23.62	23.16	26.74	30.59	30.60	26.57	28.93	26.12	28.69
Cotton acres farmed (acres)	0.04	0.04	0.04	0.05	0.05411	0.05414	0.05	0.05	0.05	0.05
% income from farming	0.76	0.73	0.72	0.82	0.9239	0.9243	0.82	0.88	0.80	0.87
Irrigation (= 1)	59.37	57.08	55.84	65.65	76.54	76.59	65.17	71.81	63.91	71.13
Crop rotation area (%)	0.62	0.60	0.59	0.67	0.76	0.76	0.67	0.72	0.66	0.72
Conservation payment (= 1)	173.82	165.37	160.87	197.67	241.58	241.76	195.81	222.08	190.95	219.35
Delta region	137.09	130.81	127.45	154.68	186.56	186.69	153.32	172.48	149.75	170.50
Southeast region	−26.44	−25.74	−25.35	−28.29	−31.24	−31.25	−28.16	−30.00	−27.79	−29.81

Notes: Entries are calculated as $100 \times [exp(\lambda_k \cdot \gamma_h) - 1]$ using the coefficients of table 4 and are interpreted as a percentage change in the log odds of adopting a technology given a one-unit change in the covariate.

Table 6. Principal Component Analysis of Adoption Rate and Technology Clustering

Technology	Component 1	Component 2	Component 3	Eigenvalue	Cumulative
Yield monitor	0.121	−0.025	0.522	9.305	0.931
Grid soil sample	−0.066	0.049	0.764	0.657	0.996
Zone soil sample	0.276	−0.014	0.258	0.036	1.000
Aerial imagery	0.403	−0.088	0.106	0.002	1.000
Satellite imagery	0.487	0.095	−0.229	0.000	1.000
Soil survey map	0.468	−0.171	0.067	0.000	1.000
Handheld GPS	0.431	0.030	−0.054	0.000	1.000
COTMAN	−0.019	0.681	0.036	0.000	1.000
Electrical conductivity	0.317	0.240	−0.070	0.000	1.000
Digital maps	0.004	0.655	0.024	0.000	1.000

adopt precision agriculture technologies. The association between the use of soil survey maps and satellite imagery was strongest. A 10% increase in income earned from farming was associated with a 9.2% increase in the odds a producer adopted these technologies. On average, for a similar change in income from farming, there was an 8.2% increase in the odds a cotton producer used the technologies analyzed here.

Technology adoption propensity scores were higher for cotton farmers who irrigated. The technologies most strongly associated with irrigation were the use of soil survey maps and satellite imagery. The odds of using these technologies increased by 77% for producers irrigating cotton. Averaging over the entries in table 5, farmers who irrigated their cotton were 66% more likely to use a combination of these technologies.

The propensity to adopt precision agriculture technologies was higher for farmers who rotated cotton with other crops. However, compared with the other loading determinants, the impact of this variable on adoption propensity was relatively small in magnitude. Taking the average over the adoption odds in table 5, cotton farmers practicing crop rotation were 0.68% more likely to use some combination of the technologies considered.

The propensity to adopt one or a combination of the technologies analyzed was greater for farmers participating in a federally sponsored working land conservation programs. This variable had the strongest association with adoption propensity scores in terms of relative magnitude. Averaging over the log-odd entries in table 5, producers participating in a working land conservation program were 201% more likely to adopt a combination of the technologies considered here.

Adoption propensity scores were higher for producers located in the Delta region but relatively lower for operations located in the southeast region.

Principal Component Analysis of Adoption Propensity Scores

Statistical grouping of the technology indicator predicted values estimated with the MIMIC model were analyzed with principal component analysis. Examination of the eigenvalues suggests that the first principal component explained 93.1% of the variation in the set of predicted values (table 6). The first two principal components account for 99.6% of the cumulative proportion of total variance. We conclude principal components 1 and 2 adequately explain the variation among the set of predicted values and focus on their relationship using a factor loading plot (figure 4).

Three technology bundles are evident in figure 4. The first, Bundle 1, includes grid soil sampling and cotton yield monitors. Grid soil sampling is one of the gateway technologies into precision agriculture. Cotton yield monitors became available by the end of the twentieth century. This pairing is consistent for gauging the relationships between soil fertility and yield. Bundle 2 includes satellite and aerial maps, handheld GPS devices, and soil survey maps. Combined, these information technologies provide a composite picture of field soil and landscape heterogeneity. The third bundle, Bundle 3, includes digitized maps and COTMAN. COTMAN is a software package designed to

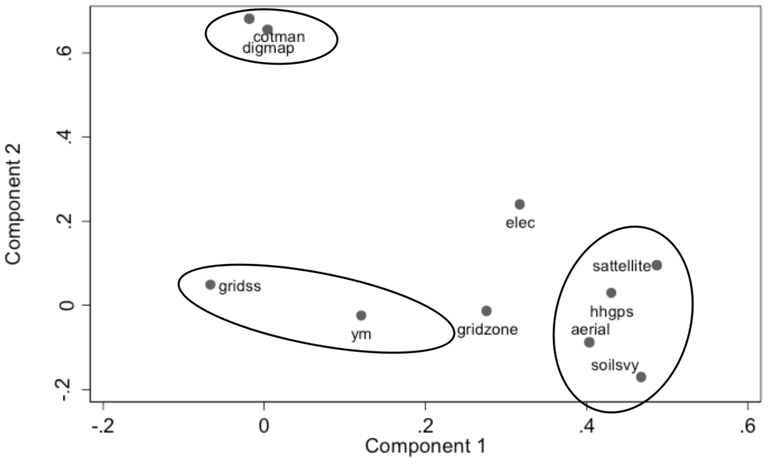

Figure 4. Component Loadings for Precision Agriculture

Notes: Rotation: orthogonal varimax.

monitor cotton boll development. The spatial and topological details provided by digitized maps could aid in identifying and documenting crop growth and development across the field.

Logistic Regression Analysis of Bundles

The discrete bundles were regressed on farm and producer attributes (table 7). Older operators were less likely to adopt the first bundle (yield monitors and grid soil sampling). For an additional information source used to understand precision agriculture technology, producers were 1.2% more likely to adopt Bundle 1. Larger cotton farms were more likely to adopt Bundle 1. For an additional 100 acres of cotton farmed, the likelihood of adopting Bundle 1 increased by 0.42%. The relative number of acres managed using crop rotation was positively correlated with the likelihood of adopting yield monitors and grid soil sampling. A 1% increase in the area managed using crop rotation was associated with a 0.1% increase in the likelihood of adopting Bundle 1. Producers participating in a working land conservation program were also more likely to combine yield monitors and grid soil sampling. Cotton producers were 5.2% more likely to use Bundle 1 if they participated in a working land conservation program.

The perception that the group of technologies analyzed were too expensive or too complex to manage decreased the likelihood that the yield monitor-grid soil sampling bundle was adopted. Producers responding that technology costs were too high to consider using a suite of these technologies were 4.6% less likely to adopt Bundle 1. Producers believing that precision agriculture technologies were too complex were 5.6% less likely to adopt the yield monitor-grid soil sampling bundle. On average, producers in the Delta region were 7.8% more likely to adopt Bundle 1, while producers in the southeast region were 5.2% less likely to adopt this bundle.

Regional covariates explained most of the variation in the adoption pattern of Bundle 2 (COTMAN and digital mapping). The covariates complexity and time consuming were omitted from the Bundle 2 regression because these variables perfectly predicted the outcome. Producers in the Appalachian and Delta region were (respectively) 2.7% and 4.4% more likely to adopt these technologies in tandem but 5.5% and 6.6% less likely to adopt Bundle 2 in the Corn Belt and southeast regions, respectively. Farm structure variables correlated with the adoption of this bundle included the percentage of income from farming and livestock ownership. Producers owning livestock were 1.4% more likely to use COTMAN with digital maps.

Bundle 3 included aerial maps, satellite maps, soil survey maps, and the use of handheld GPS devices. The variable *time consuming* was omitted from the regression because it predicted perfectly

Table 7. Logit Estimates and Marginal Effects of Farm Characteristics and Technology Bundles

	Bundle 1		Bundle 2		Bundle 3	
	Estimate	**Avg. Marginal Effect**	**Estimate**	**Avg. Marginal Effect**	**Estimate**	**Avg. Marginal Effect**
Operator education (ordinal, 1–6)	0.1056		−1.1098		0.1871	
Operator age (years)	−0.0271**	−0.0017	0.0442		−0.0046	
Information sources used (count)	0.2438**	0.0157	−0.0355		0.2642	
Cotton acres farmed (100s)	0.0651***	0.0042	0.1004		0.0461	
% income from farming	0.0023		0.0514**	0.0003	0.0134	
Owned/operated cotton area	0.0015	0.0001	0.0021		0.0106	
Livestock (= 1)	−0.1426	−0.0092	2.8394**	0.0142	0.6713	
Irrigation (= 1)	−0.0422	−0.0027	−2.0455		−0.2074	
Crop rotation area (%)	0.0163***	0.0010	−0.0446		−0.0139*	−0.0002
Cover crop area (%)	0.0040		0.0364		0.0160*	0.0002
Conservation payment (= 1)	0.8028**	0.0516	5.2617		0.2825	
Yield variability (index)	0.0018		0.0018		0.0032*	0.000041
Barrier: expensive (= 1)	−0.7196**	−0.0463	−2.3699		0.1495	
Barrier: time consuming (= 1)	0.1020		(omitted)		(omitted)	
Barrier: complexity(= 1)	−0.8717*	−0.0560	(omitted)		−0.5455	
Delta region (= 1)	1.2205***	0.0785	8.7223***	0.0435	−0.0007	
Corn Belt region (= 1)	0.5153		−10.9664***	−0.0547	0.2316	
Appalachian region (= 1)	0.2231	0.0143	5.4542***	0.0272	0.6503	
Southeast region (= 1)	−0.8039**	−0.0517	−13.1834***	−0.0657	−0.0284	
N	738		658		721	
McFadden's pseudo R^2	0.24		0.51		0.16	

Notes: Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level. Bundle 1 = yield monitor, grid soil sampling; Bundle 2 = COTMAN, digital mapping; Bundle 3 = satellite maps, handheld GPS, soil survey maps, aerial maps.

the outcome variable. Only three covariates were correlated with the adoption of this bundle, and the associations were relatively weak in magnitude and statistical significance (at the 10% level of significance).

Discussion and Conclusions

This study isolated discrete bundles of precision agriculture information technologies based on the adoption patterns of ten technologies by cotton producers. A three-step approach was used to statistically determine which precision information technologies cotton producers appear to be using in concert. In the first step, adoption patterns were analyzed using a MIMIC model. Next, the set of predicted patterns was analyzed using Principal Component Analysis (PCA) to isolate clusters of technologies used together. In the third step, the bundles identified were regressed on operator characteristics and farm structure attributes. Three discrete bundles were identified after conditioning adoption decisions on farm operator and structure covariates, which included 1) yield monitors and grid soil sampling; 2) COTMAN and digital maps; and 3) aerial, satellite imagery, handheld devices with GPS, and soil survey maps. Adoption of technology bundles was more likely for cotton growers managing relatively larger operations that used a variety of information sources to learn about precision farming. These producers also tended to irrigate their cotton, practice crop rotation, and participate in federally sponsored working land conservation programs. Operations in the Delta region exhibit a higher propensity to adopt precision information technologies.

Precision agriculture technologies may be adopted piecemeal or in bundles. Farmers adopting precision agriculture technologies may adjust their use of a technology as new information about complementary techniques becomes available. Positive experiences with so-called "gateway" precision agriculture technologies such as soil testing or use of soil survey maps may reduce the perceived risk associated with more complicated devices, eventually leading to what can be described as technology stacking (for example, see Paxton et al., 2011). The precision agriculture technology bundles analyzed here result from individual producers mixing and matching technologies and practices to maximize profit. When a producer can leverage synergies between information technologies, scale economies of information emerge, thereby lowering the costs of site-specific information needed to make important managerial decisions.

From the perspective of agribusinesses, the ability to bundle goods lowers cost and increases revenue. Other reasons agribusinesses might sell precision agriculture technologies as a package relate to the purchasing behavior of farmers. In bundling goods, the price is determined by the consumer who has the lowest willingness to pay for a good or service. When buyer markets are relatively differentiated, businesses will likely have to lower prices to remain competitive. Bundling technologies into a single package decreases preference variability. The market success of a new technology partly depends on how complementary the technology is to other aspects of the farm operation but also on the adoption rate and complexity of the technology package, which in turn increases the service provider's market share.

The approach developed in this research is novel in terms of identifying and characterizing technology adoption patterns, but other approaches could be used to analyze bundling patterns resulting from the adoption of multiple technologies. Indeed, a limitation of the MIMIC model applied here is that the coefficients associated with operator attributes and farm characteristics that determine adoption propensity are restricted to be similar across all technologies. Variation between the relationship between covariates and technologies is permitted but manifests as a difference by a scalar constant. A case-by-case analysis of the unconditional bundles using logistic or probit regression would relax this restriction. Yet correlation between the adoption choices would be compromised. Alternatively, with an additional set of assumptions, most common bundles could be analyzed using, for example, multivariate probit regression.

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