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INFORMATION SOURCES IMPACT ON THE ADOPTION OF PRECISION TECHNOLOGY BY COTTON PRODUCERS IN THE UNITED STATES

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ABSTRACT

Farmers demand more precision farming technology and specific information is consumed in the adoption process, which could not only depend on how efficiently the information flows among farmers. It is assumed that the sources of information are inputs in the production processes and could have an impact on the decision to adopt precision farming technology, after controlling for farmer and farm business characteristics. Accordingly, the objective of this research was to evaluate the effects of nine information sources used by cotton farmers of 12 U.S. producer states on the adoption of yield monitor with GPS, grid soil sampling, zone soil sampling, aerial photos, and soil survey maps. The scientific utility of this research lies on the quantitative data from the Southern Cotton Precision Farming Survey analysed using statistical methods such as univariate, bivariate and multivariate probit regressions. The statistical results indicated that information from dealers, consultants, university publications, and university events were the most common information sources used when searching for precision farming information with positive and significant effects on the adoption of precision farming technology. The presented findings from this comprehensive analysis can assist organizations in selecting information sources, and on planning communications and partnerships strategies fostering technology transfer.

Keywords: *Gossypium hirsutum* L., academic partnership, informational effects, knowledge management, knowledge transfer, technology transfer.

INTRODUCTION

In the last five decades, unprecedented technological advances have occurred in communications, precision farming, plant breeding, managerial tools, input management, industrial processing, and marketing (Mohapatra *et al*., 2018). Cotton producers have experienced gains in productivity due to those technological developments (Zhou *et al*., 2017; Gupta *et al*., 2018). Improvements in communications infrastructure have facilitated the dissemination of technology from innovators to adopters (Waters, 2013). Before the adoption

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of innovations, farmers acquire and analyse information for determining the feasibility and profitability of the new technology (Schimmelpfennig, 2016; Balafoutis, 2017). Such information may originate from different sources such as farm input dealerships, crop consultants, university extension, and media outlets (Jenkins *et al*., 2011; Edge *et al*., 2017).

Nevertheless, the contribution of different information sources to the adoption of precision farming technologies (PFT) remains not well understood nor conclusive (Erickson *et al*., 2017; Pathak *et al*., 2019). Information sources could be required for the adoption of PFT because many precision agricultural practices are more complex compared to other production technology and farm practices. It is expected that more complex technology requires a greater amount of information at various decision stages such as adoption, maintenance, and abandonment of PFT (Waters, 2013). These stages can be performed to determine profitability as decision criteria (Schimmelpfennig, 2016).

Past research on adoption of PFT through a variety of agricultural sectors has focused on understanding the effects of farmer and farm business characteristics extensively. But the role of sources of information (SI) has been neglected in the literature (Zhou *et al*., 2017). In addition, studies aimed to understand the use of SI have not evaluated their impact on adoption of PFT (Velandia *et al*., 2010; Edge *et al*., 2017). Based on previous evidence and the gaps documented in the literature, it is assumed that PFT constitute another input in the production process, and that there exists an underlying demand for such inputs according to output market conditions (Balafoutis *et al*., 2017). As farmers demand more PFT, more information is consumed in the adoption process. The adopted PFT could not only depend on how efficiently the information flows among farmers, but also on the available information sources (Velandia *et al*., 2010). Some information sources could have no effect or simply their significance may vary across PFT (Pathak *et al*., 2019). In the United States (U.S.) cotton production is economically important, with a prevalent use of PFT by farmers (Zhou *et al*., 2017; Meyer, 2018). In order to monitor PFT adoption, a comprehensive evaluation is needed, ranging from private to public, to the better understanding of the adoption of agricultural precision technology (Cisternas *et al*., 2020).

This study tested the hypothesis that the use of certain types of sources of information would positively impact the adoption of precision farming technology. The objective was to identify the sources of information used by U.S. cotton producers in 12 southern states that contribute to the adoption of precision farming technology.

MATERIALS AND METHODS

Data from the 2009 Southern Cotton Precision Farming Survey was used (Mooney *et al*., 2010). This dataset allowed evaluating a wide range of sources of information. The evaluated SI in this study included farm input dealerships, crop consultants, university extension, other farmers, trade shows, internet, news media, university publications and university educational events. To our knowledge, this is the only dataset that can allow assessing comprehensively the effects of SI on adoption of PFT; as the latest 2013 Southern Cotton Precision Farming Survey did not record SI in a way that would allow to compare and aggregate with the 2009 data or previous surveys (Mooney *et al*., 2010; Zhou *et al*., 2017).

The list of cotton farmers was obtained from the Cotton Board in Memphis, Tennessee (Mooney *et al*., 2010). The survey was mailed to 13 783 cotton producers in Alabama, Arkansas, Georgia, Florida, Louisiana, Mississippi, Missouri, North Carolina, South Carolina, Tennessee, Texas, and Virginia. The response rate was 12.5 %. The initial questionnaire was mailed on February 20, 2009, with a reminder post card sent two weeks later and a follow-up mailing to producers who had not responded on March 27, 2009 (Dillman, 1978).

The final sample contained 1098 observations corresponding to farmers who reported to have planted cotton in 2008. Binary variables were constructed for denoting the adoption of diagnostic PFT such as yield monitor with GPS, grid soil sampling, zone soil sampling, aerial photos, and soil survey maps. These are the most common adopted PFT by cotton farmers (Mooney *et al*., 2010; Zhou *et al*., 2017). Descriptive exploration of the data indicated that 71 % percent of cotton farmers were non-adopters of the five PFT considered in this study; 19 % of the farmers had adopted one PFT, 6.5 % of the farmers had adopted two PFT, and finally 3.5 % of the farmers had adopted three to five PFT.

Regression analyses

The data sources were analysed using probit regressions estimated with Stata® (Stata Corporation, 2007). Three sets of results are included to present viewpoints on the adoption process. Probit regressions were used based on the data collected and the binary nature of the dependent variables (Greene, 2003). Probit regressions are commonly applied in studies of adoption of precision farming technology because they facilitate the statistical evaluation of farm and farmer characteristics as well as specific determinant factors of interest to researchers (Zhou *et al*., 2017; Cisternas *et al*., 2020).

In the first set of results, a univariate probit regression was done. Only in this regression the dependent binary dummy variable took the value of one if the farmer adopted at least one out of five considered PFT (yield monitor with GPS, grid soil sampling, zone soil sampling, aerial photos, or soil survey maps); otherwise, it took the value of zero. Those PFT included in this analysis are the most frequently adopted by cotton farmers in the studied region (Zhou *et al*., 2017). This allowed us to gain insights from a general perspective about the effects of SI on the overall adoption of PFT.

The second analysis used a multivariate probit regression of five equations. This type of regression has been used to evaluate the use of precision farming information sources (Jenkins *et al*., 2011), because it considers the simultaneity of choices (Greene, 2003) since individuals can simultaneously use more than one production practice, information source or technology. The dependent variables adopter and non-adopter of a particular PFT were related to independent variables on farmers, farm business characteristics and SI variables. The coefficients were obtained using simulated maximum likelihood, by employing the mvprobit procedure developed by Cappellari and Jenkins (2006). The Cappellari and Jenkins (2006) routine relies on the Geweke-Hajivassiliou-Keane choice probability simulator, where the square root of the number of observations approximates the number of draws. The coefficients for the initial iterations of the multivariate estimation were calculated from univariate probit regressions. Different numbers of random draws and seed numbers were used for assessing the robustness of the estimates.

In the third analysis, the estimation of marginal effects came from bivariate probit regressions. For this analysis, focus was set on recent technology that were more likely to be adopted simultaneously, based on an evaluation of the correlation among all the dependent variables evaluated in this study. For the bivariate regressions, we studied the effects of SI on adoption of yield monitor with GPS, grid soil sampling, and zone soil sampling technology. The correlations between the dependent variables showed the importance of recent PFT such as yield monitor with GPS in comparison with aerial photos and soil survey maps (Table 1).

Independent Variables

Farmers in the survey were asked about the use of SI to gather precision farming information; explicitly they were asked: “Where do you get your precision farming information? Mark an X below each source of information you have used previously.” The available responses included farm input dealerships, crop consultants, university extension, other farmers, trade shows, internet, and news media; binary dummy variables were used to typify these SI.

Table 1. Correlations of adopted precision farming technology.

	Yield monitor with GPS	Grid soil sampling	Zone soil sampling	Aerial photos	Soil survey maps
Yield monitor with GPS	1				
Grid soil sampling	0.2731	1			
Zone soil sampling	0.1599	0.1411	1		
Aerial photos	0.1297	0.0930	0.2591	1	
Soil survey maps	0.1377	0.1453	0.2234	0.3235	1

N = 1098 observations.

University extension is interpreted as the information provided by university extension personnel. Only 13.4 % of surveyed farmers indicated having used one source of information for precision farming decisions, 56 % between two and four SI, and finally 17 % of the farmers used between five and seven SI.

Farmers indicated having obtained information about precision farming from university publications and university educational events; in the sample, 34.7 and 48.4 % of cotton producers indicated having used those SI in the past five years, respectively. The corresponding questions in the survey were as follow: "Have you used university publications to obtain precision farming information in the past five years?" and "How many times have you attended university educational events or presentations related to precision farming in the past five years?" The inclusion of these information sources increases our understanding of the role of universities as sources of information about precision farming technology beyond university extension personnel and other SI such as farm input dealerships, crop consultants, extension, other farmers, trade shows, internet, and news media.

A binary dummy variable was introduced for evaluating the incidence of university publications on the adoption of PFT whereas the influence of university educational events was evaluated by the number of attended events related to precision farming during the last five years (Table 2). The Pearson correlation coefficients between extension, use of university publications, and attendance to university educational events were below 0.28, guaranteeing the necessary condition of independence of those variables in the regressions. The variance inflation factors and the condition numbers did not diagnosed multicollinearity among the independent variables.

The use of computers was included in two separate independent variables: the use of a computer for farm management and for field work. About 54 % of cotton producers employed computers for management purposes while only 12.7 % of surveyed farmers stated having used computers for field operations (Table 2). The average farm size was approximately 327 ha, one third of that land was reported as rented.

The average age of the respondents was 55 years, with an average of 30.6 years of farming experience. On average, farmers had 14.3 years of education. Off farm income by cotton producers accounted for 25.1 % of total income. Two thirds of the survey respondents had incomes below USD $149 000 in 2007 (Table 2). The impact of farm location on precision farming adoption was assessed by using binary dummy variables indicating the state where the farm is located (Alabama, Arkansas, Florida, Georgia, Louisiana, Missouri, Mississippi, North Carolina, South Carolina, Tennessee, Virginia, and Texas). The binary dummy variable associated with farms located in Texas was excluded from the analysis to avoid multicollinearity problems (Jenkins *et al.*, 2011. Farms located in Texas represented 47.5 % of farmers in the dataset (Table 2).

Table 2. Definition of variables and corresponding descriptive statistics.

Variable	Description	Mean	Weighted Mean
Precision Farming Technologies			
Yield monitor-GPS	=1 for adoption of yield monitors with GPS[†]	0.055	0.037
Grid soil sampling	=1 for adoption of grid soil sampling[†]	0.132	0.109
Zone soil sampling	=1 for adoption of zone soil sampling[†]	0.148	0.126
Aerial photos	=1 for adoption of aerial photos[†]	0.042	0.032
Soil survey maps	=1 for adoption of soil survey maps[†]	0.062	0.05
Sources of Information:			
Dealers	=1if information from farm dealers was used[†]	0.617	0.568
Consultants	=1if info. from crop consultants was used[†]	0.302	0.279
Extension	=1if info. from extension was used[†]	0.381	0.363
Farmers	=1if info. from fellow farmers was used[†]	0.589	0.572
Trade shows	=1if info. from trade shows was used[†]	0.309	0.289
Internet	=1if info. from internet was used[†]	0.25	0.224
News media	=1if info. from news media was used[†]	0.338	0.337
University events	Attended number of events	2.643	0.313
University publications	=1 if university publications were used[†]	0.347	2.443
Controls:			
Computer for management	=1 if there was computer for farm management[†]	0.541	0.472
Computer on field	=1 if there was computer usage in the field[†]	0.128	0.096
Farm size	Hectares planted with cotton	326.6	238
Percent of rented land	Rented land planted with cotton (percentage)	65.099	62.892
Age	Farmer's years of age	54.87	55.838
Farming experience	Years of farming experience	30.631	30.641
Years of schooling	Years of schooling	14.298	14.118
Income category	=1 if total income was above $149 999[†]	0.347	0.297
Farming income	Income fraction from farming (percentage)	74.872	68.765
AL	=1 if farm was located in Alabama[†]	0.051	0.048
AR	=1 if farm was in Arkansas[†]	0.033	0.052
FL	=1 if farm was in Florida[†]	0.017	0.012
GA	=1 if farm was in Georgia[†]	0.087	0.131
LA	=1 if farm was in Louisiana[†]	0.042	0.038
MO	=1 if farm was in Missouri[†]	0.021	0.032
MS	=1 if farm was in Mississippi[†]	0.06	0.053
NC	=1 if farm was in North Carolina[†]	0.114	0.083
SC	=1 if farm was in South Carolina[†]	0.032	0.033
TN	=1 if farm was in Tennessee[†]	0.051	0.034
VA	=1 if farm was in Virginia[†]	0.017	0.015
TX	=1 if farm was in Texas[†]	0.475	0.469

[†] =1: It indicates the condition for the values of 1 for the binary dummy variable.

Supplementary weighted results were obtained as a robustness check of the presented results, given the low response rate and the fact the size of farms represented in this survey tend to be bigger than the average size of cotton farms in the surveyed states based on the 2007 U.S. Department of Agriculture census data (Lambert *et al*., 2014). The weights in this study were "ranking" weights as applied by Singh et al. (2001) which were estimated by iteratively normalizing cell weights by the Cartesian product of the marginal row (cotton farm size) and column (state cotton farm numbers) totals from the population of cotton farms according to the USDA Agricultural Census (Lambert *et al*., 2014). The observations were grouped into 72 classes corresponding to the 12 states and six farm size classes. The estimated weighted regressions did not differ from the non-weighted regressions, thus, in the next section we present the results using the original data.

RESULTS AND DISCUSSION

This study presented three empirical analyses to assess the effects of SI on the adoption of PFT. In the first analysis, univariate probit regressions were used to evaluate the effect of SI on the adoption of PFT without specifying a particular technology. The second analysis, a multivariate probit regression to evaluate the effect of SI on the adoption of five PFT yield monitor with GPS, grid soil sampling, zone soil sampling, aerial photos, and soil survey maps) was used, allowing for these technologies to be simultaneously adopted by the farmer. The third analysis used bivariate probit regressions to evaluate the influence of SI on the adoption of PFT that were more likely to be adopted simultaneously by a large percentage of respondents (yield monitor with GPS, grid soil sampling, and zone soil sampling technology). Therefore, results of each analysis have different meaning and interpretation.

Results from the univariate probit regression implied that in general SI have positive effects on the adoption of the analysed PFT as it was expected. This statistical evidence provided support for the hypothesis that SI had an effect in the process of adoption of agricultural precision technology. The use of information from farm input dealerships had positive and significant effects on the overall adoption of precision farming practices; the marginal effect of 8.5 % was significant ($p \leq 0.01$). Information from university publications ($p \leq 0.01$) and attendance to university educational events organized by universities ($p \leq 0.05$) also had positive effects on the adoption of PFT (Table 3). These findings provided evidence of the important role university extension play in the adoption of precision farming technology. In terms of the magnitude of probability changes, the greatest marginal effect on adoption of PFT was university publications followed by information provided by farm input dealerships and trailed by the effects of university events (Table 3).

The use of university publications for obtaining precision farming information increased the probability of adoption by 11.3 %, while the use of farm input dealerships increased the probability of adoption by 8.5 %. Attending an additional event increased the probability of adopting PFT by about 0.5 % (Table 3). Each additional year of education increased the chances of adoption by about 1.13 % ($p \leq 0.1$), while the increase of 1 % in the fraction of farm

Table 3. Marginal effects for the overall adoption of precision farming technology.

Independent variables	Marginal effect	Standard error	Probability value
Dealers	0.08496	0.03196	0.0080
Consultants	0.00954	0.03349	0.7760
Extension	-0.00331	0.03286	0.9200
Farmers	0.00464	0.03119	0.8820
Trade shows	0.00479	0.03161	0.8790
Internet	0.02947	0.03798	0.4380
News media	0.04977	0.03172	0.1170
University events	0.00502	0.00248	0.0430
University publications	0.11271	0.03382	0.0010
Computer for management	0.03831	0.03228	0.2350
Computer on field	0.04070	0.04323	0.3460
Farm size	0.00005	0.00005	0.3330
Percent of own land	0.00022	0.00040	0.5810
Age	-0.00081	0.00214	0.7040
Farming experience	-0.00359	0.00198	0.0690
Years of schooling	0.01125	0.00629	0.0740
Income category	0.01341	0.02954	0.6500
Farming income	0.00203	0.00055	0.0000
AL	0.09271	0.07254	0.2010
AR	0.15514	0.08673	0.0740
FL	0.05557	0.10698	0.6030
GA	0.21336	0.06414	0.0010
LA	0.49055	0.07439	0.0000
MO	0.13291	0.13275	0.3170
MS	0.29992	0.07964	0.0000
NC	0.22689	0.05625	0.0000
SC	0.28888	0.11412	0.0110
TN	0.20617	0.08343	0.0130
VA	0.01047	0.08229	0.8990

Variable estimates were generated using probit regression; the dependent variable took the value of one if the farmer adopted at least one of the five PFT considered (yield monitor with GPS, grid soil sampling, zone soil sampling, aerial photos, or soil survey maps), otherwise, it was zero. In the sample of 1098 observations, there were 28.87% farmers classified as adopters of at least one precision farming technology. The marginal effects were estimated at mean points of the independent variables.

income to the overall income increased the chances of adopting PFT ($p \leq 0.01$) by about 0.20 % (Table 3). There were significant regional differences; for example, farmers located in Louisiana were 49 % more likely to adopt PFT than farmers located in Texas (Table 3).

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In the second analysis, the effects of SI on each selected PFT were evaluated using a multivariate probit regression. After controlling for farmer and farm business characteristics, the adoption of PFT was positively impacted by SI at varying levels of significance (Table 4). Attendance to organized events by universities had significant effects on the adoption of yield monitors with GPS ($p \leq 0.05$), as well as on the adoption of aerial photos and soil survey maps ($p \leq 0.1$). The use of university publications was a significant factor influencing

Table 4. Parameter estimates for adoption of precision farming technology from multivariate probit regression.

Independent variables	Yield monitor with GPS	Grid soil sampling	Zone soil sampling	Aerial photos	Soil survey maps
Dealers	0.1497	0.2149 c	0.2928 a	0.0012	0.2928 c
Consultants	-0.2099	0.2051 c	0.078	-0.2675	0.113
Extension	0.2061	0.0624	-0.0417	-0.0557	-0.0644
Farmers	0.1464	-0.0442	0.0897	0.0987	0.0381
Trade shows	0.1301	0.1361	0.0728	0.1574	0.0587
Internet	0.3493 c	0.0776	0.0202	0.1169	0.5054 a
News media	-0.2538	-0.1277	0.2228 b	0.4074 a	0.1061
Univ. events	0.0248 b	0.008	0.0139 c	0.0189 c	0.0179 c
Univ. publications	0.066	0.3873 a	0.2294 b	0.2142	0.1882
Computer/anagement	0.5380 b	0.4929 a	-0.1079	0.1988	-0.0323
Computer/field	0.5794 a	-0.1982	0.1879	0.3795 b	0.1501
Farm size	0.0005 a	0	0	0.0003 c	0
Percent of rented land	0.0001	-0.0030 c	0.0018	0.0028	0.0016
Age	-0.0095	0.039	-0.0025	-0.003	-0.0153
Farming experience	0.003	-0.0145	-0.0042	-0.0113	0.0071
Years of schooling	0.0103	0.039	0.0629 a	0.0034	0.0464
Income category	-0.1147	-0.1616	-0.0101	0.0126	0.1268
Farming income	0.0123 a	0.0073 a	0.0047 b	0.0066 c	0.0059 c
AL	0.7993 b	0.3322	0.4694 b	0.3977	0.8234 a
AR	1.4720 a	1.1714 a	0.3052	0.2291	-3.8071
FL	0.5309	1.2824 a	0.1543	-4.7619	-3.8214
GA	0.1245	0.8136 a	0.7887 a	-0.2564	0.3075
LA	1.6691 a	1.2819 a	0.7069 a	0.7971 a	1.0052 a
MO	0.5274	1.0362 a	0.2409	0.586	-0.0575
MS	1.4542 a	1.4109 a	0.1538	0.6799 b	0.7572 a
NC	0.7174 a	0.7829 a	0.5052 a	0.5514 b	0.9283 a
SC	0.3828	0.8752 a	0.6162 b	1.0096 a	1.1649 a
TN	0.9592 a	1.2599 a	0.2448	0.0061	0.2704
VA	1.1813 a	0.433	0.6144 c	-0.1036	1.3076 a
Constant	-4.1964 a	-2.9019 a	-2.9848 a	-3.0440 a	-3.3880 a

Sample size=1098. Number of draws=30, as recommended by Cappellari and Jenkins (2006). Overall model significance - Wald Chi^2 (145) = 407.47. Significance of the overall off-diagonal correlation structure - LR Chi^2 (10) = 88.5223. The letters a, b, and c indicate estimates are statistically different from zero at $p \leq 0.01$, $p \leq 0.05$, and $p \leq 0.10$, respectively.

the adoption of grid ($p \leq 0.01$) and zone soil sampling ($p \leq 0.05$) (Table 4). The adoption of zone soil sampling was significantly influenced by information from farm input dealerships (Table 4).

The adoption of soil survey maps was influenced by information originating from farm input dealerships and the internet. In addition, the adoption of aerial photos was influenced only by the presence of information from news media. As a result, it is inferred that SI have different effects on the adoption decision depending on the PFT being evaluated, possibly due to different degrees of complexity and investment requirements (Table 4). The binary dummy variables assigned to the states where farms were located had significant effects on adoption of PFT, implying there were differences in adoption rates based on location (Mooney *et al*., 2010) (Table 4).

The estimated marginal effects from the third analysis, the bivariate probit regression, indicated that the probability of adoption of yield monitor with GPS increased by 0.2 % for every university event that the farmer attended ($p \leq 0.1$). Results also suggested that the use of information from university publications increased the probability of adopting grid soil sampling technology by 14 % ($p \leq 0.05$), while the use of precision farming information from consultants increased its adoption by 11 % ($p \leq 0.1$) (Table 5). For the case of soil sampling adoption, it was 9 % more likely to be adopted when dealers were used as a source of precision farming information. The use of university publications increased the probability of adoption by 7.5 % ($p \leq 0.1$); while news media increased ($p \leq 0.05$) this probability by 10 % (Table 5). The adoption of yield monitor with GPS was 1.4 % more likely with an additional university event attended conditional on the adoption of zone sampling technology ($p \leq 0.1$).

The three presented statistical regression analyses provided support for the hypothesis that sources of information positively influence the adoption of precision farming technology. This study has shown that university publications and attendance to university educational events had positive and significant effects on the adoption of PFT. These SI had not received attention before in the literature of precision faming technology adoption (McBride and Daberkow, 2003; Lambert *et al*., 2014).

Information from dealers and consultants had the expected positive and significant effects on adoption, in contrast to university publications and education events, the effects of these SI were not regularly significant across all the regression results. The presented statistical evidence supported the hypothesis of this study, even though the effects of SI vary across PFT. These results implied that studying specific technology is recommended rather than bundles of PFT (Cisternas *et al*., 2020). Therefore, studying disaggregated SI is more informative than SI analysed on broad categories (McBride and Daberkow, 2003; Velandia *et al*., 2010).

These results suggested that universities play an important role in disseminating objective information demanded by farmers. Universities

Table 5. Marginal effects of information sources on adoption of precision farming technology.

Sources of information	Yield monitor with GPS	Grid soil sampling	Zone soil sampling
Dealers	0.0060	0.0659	
Consultants	-0.0257	0.1102 b	
Extension	0.0220	-0.0075	
Farmers	0.0193	-0.0369	
Trade shows	0.0136	0.0327	
Internet	0.0389	-0.0129	
News media	-0.0230	-0.0125	
University events	0.0023 b	-0.0003	
University publications	-0.0081	0.1399 a	
Dealers	0.0053		0.0914 a
Consultants	-0.0113		0.0445
Extension	0.0129		-0.0330
Farmers	0.0075		0.0190
Trade shows	0.0120		0.0131
Internet	0.0250		-0.0197
News media	-0.0194		0.1022 a
University events	0.0014 b		0.0030
University publications	0.0004		0.0749 b

Marginal effects of sources of information were estimated at the means of the independent variables from bivariate probit regressions (adoption of yield monitor with GPS with grid soil sampling, and yield monitor with GPS, and zone soil sampling). The letters a and b indicate estimates are statistically different from zero at $p \leq 0.05$ and $p \leq 0.10$, respectively.

have high credibility as a source of information among farmers because they provide objective information linked to research results and not subjected to the interest of companies on selling technology, products, and services. This credibility has been the product of an established long-term relationship based on trust, constant support, and effectiveness as perceived by the reliability and relevance of information provided over decades of continuous service (Jenkins *et al*., 2011; Mohapatra *et al*., 2018). Considering that university extension is significantly influencing PFT adoption, providers of PFT and government agencies should foster stronger partnerships with them (Warner *et al*., 2017; de Wit-de Vries *et al*., 2019).

Previously discussed results indicate that private SI were also significant factors in the adoption of PFT; for instance, information from farm input dealerships, consultants and news media were the resources that had positive and significant influence on the adoption of the PFT. These results were consistent with the findings of McBride and Daberkow (2003) and Edge *et al.* (2017) who have pointed out the increasing importance and usage of input suppliers as private sources of information. This suggests that stronger and more active cooperation between the public and private sector is recommended, given that broader extension services provided by universities and private SI are contributing factors to the adoption of PFT.

Even though the utilized dataset contained more than a thousand observations from surveyed cotton farmers, this research may incentivize data collection on a wider variety of sources of information such as social networks (Yaseen *et al.*, 2018). In addition, data collection must be consistent across time periods to continue investigating the effects of information on adoption of PFT considering the farm data lifecycle (Thompson *et al.*, 2021). This will allow researchers to monitor changes in preferences for sources of information and their effects. However, it is expected that the new findings may not differ from those presented, especially the statistically significant effects for the most recent technologies (Miller *et al.*, 2017).

Further surveys aiming at the understanding of adoption of PFT are advisable; as well as to consider gathering data on farmers using information that comes from partnerships among private and public sources. Such new data may assist institutions and manufacturers of PFT to adapt their strategic communication plans on different geographic locations (Bressler *et al*., 2021).

CONCLUSIONS

Statistical support was obtained through this study for the notion that public and private sources of information contributed positively to the adoption of precision farming technology after controlling for farm and farmers characteristics. Attendance to university events and use of university publications were important sources of information impacting significantly the adoption of precision farming technology. Thus, emphasizing the relevance of universities extending information, which exerts an important influence on the adoption of technology, such as yield monitor with global position systems, grid soil sampling, and zone soil sampling technology.

Private information sources were also important and significant suppliers of information for cotton farmers. Private sources of information such as farm input dealers, consultants and news media positively influenced the adoption of precision farming technology. Consequently, public information sources together with private suppliers of information had become the channels of communication between the manufacturers of precision farming technology and the farmers.

The use of these private and public information sources impacted positively the technology implementation decisions in the US cotton production sector. It is also apparent, that input suppliers and manufacturers of precision farming technology would benefit from strategic partnerships with universities and their extension specialists, more involved with farmer communities. Due to their proficiency and experience in understanding the function of information in a knowledge-driven economy.

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