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Determinants of Irrigation Technology Adoption and Acreage Allocation in Crop Production in Louisiana, USA

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Abstract: This study identifies the determinants of furrow irrigation technology adoption in soybean production. Further, it estimates and evaluates the determinants of acreage allocation under different irrigation technologies in Louisiana crop production. Through a comprehensive mail survey, we acquired the necessary data, employing them to conduct IV-probit estimations specifically focused on irrigation technology adoption. Simultaneously, we utilized the same dataset to deploy multivariate fractional regression models, facilitating a robust exploration and evaluation of the acreage allocation of crop production in the state. The estimated results indicate that education has a significant negative effect on furrow irrigation adoption, while laser leveling has a significant positive effect on it. In particular, the expected probability of furrow irrigation adoption by farmers with a college degree or higher is 45% lower than farmers with education below the college degree. Education, risk attitude, and landholding have a negative effect, and rent status and have a positive effect on acreage allocation under the furrow irrigation system. Our study implies that appropriate policy tools may motivate farmers to adopt cost-effective as well as water-conserving irrigation technology.

Keywords: acreage allocation; instrumental variable; irrigation technology; Louisiaa; soybean; survey

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1. Introduction

The humid subtropical climate of Louisiana, USA, typically gets ample rainfall, and water availability has not historically been a major concern. Groundwater is the primary source of irrigation water in the state. Some aquifers in the state are showing signs of stress due to over-extraction as evidenced by the presence of cones of depression (examples include the Sparta Aquifer, Mississippi River Alluvial Aquifer (MRAA), and Chicot Aquifer) [1–3]. A report produced by Sargent [4] in cooperation with the United States Geological Survey (USGS) indicates that the groundwater withdrawals for general irrigation increased in 37 of the 64 parishes (Parish is a geographical unit similar to county in other U.S. states) in Louisiana by 58% from 2005 to 2010. As of 2018, 71.8% of the total Louisiana corn area and 42.8% of the total soybean area were irrigated. At the same time, the state had 55.8% of total agricultural land in the farm under irrigation [5].

Irrigation has been increasingly used by farmers as a risk management strategy in crop production in Louisiana. The continuous over-extraction of groundwater has two implications. The first is that the energy cost required for groundwater pumping increases as groundwater levels decline. The second implication is that a reduced water table, in the long run, may cause saltwater intrusion in some aquifers, as has been observed in some cells of two major aquifers (Chicot and MRAA). To avoid such risk becoming widespread and catastrophic, a serious effort is required to maintain a water table balance to ensure sustainable groundwater use.

Producers' irrigation behavior and their irrigation technology adoption decisions are determined by many factors, such as land characteristics, weather factors, crop selection, farm operation cost, water availability, energy cost, and perception about sustainability. On the one hand, producers are more concerned about the present level of productivity and net on-farm profitability. On the other hand, the resource sustainability perspective aims to minimize water use while maintaining the required level of moisture for crop growth. Farm irrigation practices among the farmers seem analogous to these two contrasting perspectives. For instance, center-pivot irrigation technology is more efficient in water application than the commonly used furrow irrigation system [6]. However, farmers can be reluctant to switch to a more efficient irrigation technology when initial investment costs are high, especially when there are no restrictions on groundwater withdrawal amounts.

Many studies have been conducted regarding the evaluation of determinants of irrigation technology adoption in different parts of the world. In most cases, water availability, extension services, cropping patterns, and educational levels were important variables affecting irrigation technology adoption. He et al. [7] find that farmers' educational backgrounds, farm labor availability, the extension service, and positive attitudes towards irrigation technology adoption are the major variables determining the adoption of rainwater harvesting and supplementary irrigation technology. Namara et al. [8] find that groundwater availability, cropping patterns, credit access, the level of education, and financial status are the most influential factors for adopting the micro-irrigation method. Feike et al. [9] indicate that farm size, crop types, and cropping intensity were the major determinants of drip irrigation technology adoption for cotton farming in the arid area of China. Dai et al. [10] determine that the reliability of the water source, government promotional activities, the level of education, soil texture, energy price, and the availability of farm labor were positively associated with the adoption of irrigation technology in the Heilongjiang province of China. In another context, Song et al. [11] and Li and Zhao [12] note that the adoption of a more efficient irrigation technology led to rebound effects (the expansion of irrigated areas previously not under irrigation).

Information channeling and social capital are important factors in explaining technology adoption decisions by farmers. Information dissemination concerning new studies and findings through effective and reliable sources can optimize its implementation probability and thus be productive in achieving the goal of resource management. Hunecke et al. [13] demonstrate that trust in the institution (Note that formal networks represent the farmers' participation in associations and meetings with professionals and experts; informal networks represent networks of close neighbors, family, and friends; general trust refers to trust in the surrounding society, such has family, friends and colleagues; and two types of irrigation technologies are drip or sprinkler with/without scheduling adoption) and formal and informal networks positively influence irrigation technology adoption in Central Chile. (In specific term, it refers to water board that controls the irrigation water use in a specific geographic region of many countries in the world. In broader context, the term represents governmental regulatory and research entities involved in water resource monitoring, evaluation, and regulation as well in many counties depending on the water resource availability) A study conducted by Krishnan and Patnam [14] in Ethiopia reveals that the extension service was more effective during the initial phase of new production technology adoption. However, social learning is far more persistent and impactful throughout the adoption process than the extension service alone. While the extension service and social learning have individually been shown to be influential in irrigation technology adoption, their influence is increased when these mechanisms for information dissemination are combined [15].

Using efficient irrigation technology is generally viewed as feasible to reduce consumptive water for agricultural production. However, it is shown that the conversion to a more efficient irrigation technology increased groundwater extraction in western Kansas [16]. These findings, which other studies have supported, imply that adopting an efficient irrigation technology is a necessary but not sufficient condition for water conservation. For instance, Segarra and Feng [17] observe that declines in irrigated acres in the Texas High Plains were due to low-efficiency irrigation technologies combined with low crop prices resulting in low farm profitability. In the context of the U.S. Pacific West, producers' irrigation decisions are determined by economic and physical water scarcity, climate, and extreme weather such as severe drought, frost, and extreme heat [18]. Additionally, in regions where groundwater supply is significantly low, converting from an inefficient gravity irrigation system to an efficient drip irrigation system offsets many of the negative impacts of drought on farm income, as explained by Ward [19] in the context of the Rio Grande River Basin of New Mexico.

Many studies [20–23] have evaluated the determinants of irrigation technology adoption for different crops in different geographic locations in the U.S. Producers intend to adopt new technologies to hedge against yield uncertainty caused by frequent drought periods, in which the farmer's human capital plays a significant role in the decision to adopt modern and more efficient irrigation equipment [24].

Bryant et al. [25] determine the effect of integrating irrigation water management practices on irrigation water use, soybean yield, irrigation efficiency, and net returns in the prairie region of Arkansas and the delta region of Arkansas and Mississippi. They find that, compared to conventional irrigation practices, irrigation water management practices reduced total water use by 21% and increased water use efficiency by 36%, and sensor-based scheduling reduced the number of irrigations by 50%. But in the context of Arkansas, Huang et al. [26] find that producers are more likely to rely on water management practices (moisture sensors, flow meters, etc.) instead of more efficient irrigation technologies. From the literature we reviewed, we note that limited studies have been carried out concerning the determinants of irrigation technology adoption and acreage allocation in regions similar to Louisiana. This study contributes to the literature by filling this research gap.

The main objectives of this study are to determine the factors affecting irrigation technology adoption and acreage allocation for different irrigation technologies among soybean producers in Louisiana. For this purpose, we conducted a farm-level survey to collect information regarding irrigation practices and concerns. The instrumental variable probit (IV-probit) model is used to estimate the determinants of irrigation technology adoption for soybean irrigation. A multivariate fractional regression method was used to estimate the determinants of acreage allocation. To the best of our understanding, except for Huang et al. [26] in Arkansas, this issue has not been evaluated in the context of the southeastern region of the U.S. (as defined by the USGS) using farm-level survey data. Our study area could be a representative region for many parts of the world that have characteristics similar to the southeastern region of the U.S. The findings of this study should be beneficial to those concerned about water productivity, water resource conservation, and sustainable farming. The results can help formulate policies to promote efficient irrigation technology adoption.

The remainder of this paper is structured as follows. Section 2 provides details on the survey used and data description. Section 3 describes the model specification and estimation methods, including probit and IV-probit models for the adoption of irrigation technology and a multivariate fractional regression method for acreage allocation. Section 4 presents empirical results, policy implications, and discussion. Section 5 provides concluding remarks and future directions.

2. Survey and Data Description

We conducted a survey to understand irrigation practices and the concerns of Louisiana soybean farmers for the 2015 crop year following Dillman's [27] tailored design method. Considering the sampling adjustment in the 2015 crop year survey, 158 responses were received from a total survey sample of 2432, for a response rate of 6.5 percent. However, given the low number of respondents who provided complete information in that initial survey, the survey was redesigned without changing the central theme and was sent out again in the 2016 crop year. In this second round of the survey, we sent out a pre-notification letter (postcard) to 1680 Louisiana soybean producers (Figure 1). Out of the total questionnaires sent out, 451 envelopes were returned because of address errors or because some of the farmers had retired. From the total sample of 1229, considering the sampling adjustment, we obtained 123 responses. The response rate for the second round of the survey was 10 percent, 3.5 percent more than the first round of the survey conducted for the crop year 2015. We did not send questionnaires in 2016 to those farmers who responded in the 2015 survey to avoid the possibility of repetition.

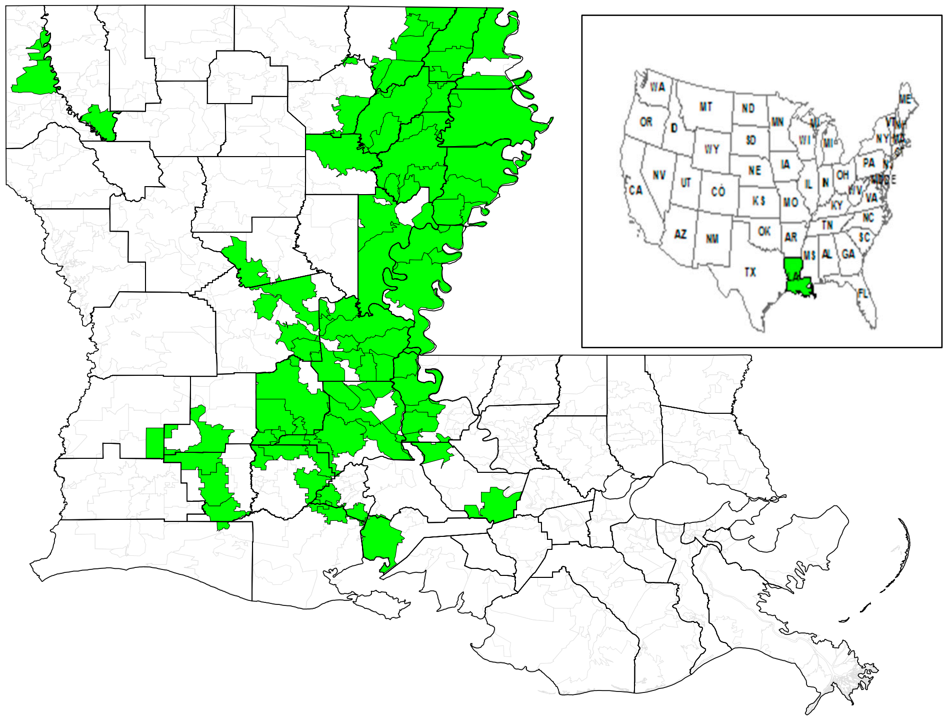

Figure 1. Respondents' farm locations in Louisiana (the green color indicates where respondents are located).

Survey questions were related to irrigation water quality, technology adoption, water availability, future concerns about crop irrigation, and the sociodemographic characteristics of farm producers. Table 1 presents the variables used, variable definition, and descriptive statistics used in different regression models.

Table 1. Descriptive Statistics.

Variable	Variable Definition	Obs	Mean	SD
IRSOY	Soybean irrigation (furrow = 1, other = 0)	242	0.455	
FRFLD	Fraction of flood irrigation	242	0.092	0.675
FRFUR	Fraction of furrow irrigation	242	0.392	0.915
FRCPV	Fraction of center-pivot irrigation	242	0.066	0.136
FRNIR	Fraction of non-irrigated acres	242	0.451	0.414
EDU2	Farmers' education (high school)	232	0.328	0.470
EDU3	Farmers' education (some college degree)	232	0.233	0.424
EDU4	Farmers' education (college degree)	232	0.306	0.462
EDU5	Farmers' education (grad. or professional degree)	232	0.091	0.288
FARMREV1	Total farm revenue fraction (USD 0–100,000)	226	0.518	0.501
FARMREV2	Total farm revenue fraction (USD 100,000–500,000)	226	0.261	0.440
RISKD2	Risk aversion	172	0.390	0.489
RISKD3	Risk neutral	172	0.378	0.486
ENGC	Total energy cost (in U.S. dollars)	242	6218.66	14,793.62
EXPNC	Farming experience (in years)	204	31.343	14.229
EXTS	Extension as information source (1,0)	242	0.450	

Table 1. *Cont.*

Variable	Variable Definition	Obs	Mean	SD
NBRS	Neighbors as information source (1,0)	242	0.240	
DSTED	Distance to equipment dealer (in miles)	217	14.677	9.871
LASER	Laser leveling (1,0)	221	0.407	
EDSP2	Spouse education (high school)	188	0.319	0.467
EDSP3	Spouse education (some college degree)	188	0.170	0.377
EDSP4	Spouse education (college degree)	188	0.324	0.469
EDSP5	Spouse education (grad. or professional degree)	188	0.165	0.372
ACRE	Total acres of land (land holding in acres)	235	1395.85	2494.12
RENT	Status of rent (1,0)	242	0.583	
DSTON	Distance to town (in miles)	216	8.428	8.265

Notes: EDU is a dummy variable representing an educational attainment of a college degree or above and below college degree (1,0); FARMREV1 = farm income less than USD 0–100,000; FARMREV2 = income between USD 100,000–500,000; and FARMREV0 = income more than USD 500,000 (which is not stated in the table). The variable EXTS stands for only extension service and NBRS stands for only neighbors as the source of information.

The dependent variables are arranged to make it appropriate for two different models. In irrigation technology adoption estimation, the dependent variable is a dummy variable that represents furrow and other irrigation (1 for furrow including flood irrigation and 0 for other irrigation technology as a dependent variable) in soybean production. The main reason for considering a binary form of irrigation technologies is the limited number of samples and a higher percentage of furrow irrigation users in soybean and corn production. It is well accepted that the furrow irrigation technology is less efficient than the center-pivot irrigation technology. However, furrow irrigation with submersible electric well and poly-pipe has expanded extensively over the past 10 to 15 years in the state's major corn and soybean growing areas in the Mississippi River Alluvial Aquifer in North Louisiana. As a result, the state has seen a steady decline in the aquifer level in this area. Table 1 shows that, on average, 45% of respondents had adopted furrow irrigation in soybean production.

The dependent variables for the multivariate fractional regression model are fractions of irrigated acres under different irrigation technologies. Indeed, furrow and flood irrigation are almost the same. However, due to the response obtained from farmers, we grouped them into two categories. The primary consideration here is determined by the use of poly-pipe. Furrow irrigation refers to one that uses poly-pipe and flood irrigation refers to gravity irrigation without using poly-pipe. The four categories of fractions included flood-irrigated (9% of total acres), furrow-irrigated (39% of total acres), center-pivot-irrigated (6.6% of total acres), and non-irrigated acres (45% of total acres). These values consider all irrigated and non-irrigated acres under operation across all commodities (corn, soybeans, cotton, and rice). The educational background of the principal farm operators was found to be 32% with a high school degree, 23% with some college, 30% with a bachelor's degree, and 9% with a graduate or professional degree. These were then regrouped into two categories (some college or less and a 4-year degree or more) representing the "EDU" variable. Survey results indicated that 51% of the operations had a total farm income during the crop year of below USD 100,000, while 26% had a total income between USD 100,000 and USD 500,000, and 23% had annual total farm income of above USD 500,000. The risk variable represents the farmer's attitude towards an investment decision. The risk aversion, risk-neutral, and risk-loving information was elicited by asking whether the producers tend to avoid risks whenever possible in their investment decision. As shown, 39% of respondents were identified as risk-averse, 37% as risk-neutral, and 24% as risk lovers. Extension and neighbors are dummy variables representing the sources of information that farmers rely on for water conservation or irrigation cost reduction information. As seen from Table 1, roughly 45% of the respondents rely on the extension service, while 24% rely on neighbors for the farm information source. We can also observe that around 58% of respondents are farming rented farmland (leasing in). Other variables used in this study are the distance to the nearest market or town, distance to the nearest equipment dealer, energy cost, and spousal educational attainment.

3. Method

3.1. Irrigation Technology Adoption

In our survey, most farmers indicated that they use furrow and center-pivot irrigation technologies in soybean and corn production. Since the outcome variables are binary, a probit regression approach is utilized to estimate the determinants of irrigation technology adoption. The probit regression is based on the random utility model in which an individual farmer's decision depends on the difference in the marginal benefit of choosing an alternative irrigation technology. This difference in marginal benefit, denoted by y^*, is not observable. However, the final outcome is observed, as the individual would choose a particular option if it provided higher utility, that is $y = 1$ if $y^* > 0$ and $y = 0$ otherwise [28]. Here, $y = 1$ refers to the outcome when an individual farmer adopts the furrow irrigation technology. Many factors determine this selection of irrigation technologies. The model can be expressed as:

$$Pr(y = 1|X) = F(\beta_0 + \beta X_i) \quad (1)$$

where, Pr is the probability of adoption, F is the cumulative distribution function assumed to be normally distributed, X is the vector of explanatory variables, and β is the parameter to be estimated.

An endogeneity problem arises when one or more explanatory variables are correlated with the error term. We can use an instrumental variable probit model that fits with dichotomous dependent variables and endogenous regressors to correct that problem. The general specification of the model can be expressed as:

$$y_{1i} = x_{2i}\alpha + x_{1i}\beta + e_i \quad (2)$$

$$x_{2i} = x_{1i}\mho_1 + \mathrm{z_{2i}}\mho_2 + \varepsilon_i \quad (3)$$

In Equations (2) and (3), x_{2i} is the $1xm$ vector of the endogenous variable, x_{1i} is a vector of exogenous variables, and z_{2i} is a vector of instrumental variables. It is assumed that $(e_i, \varepsilon_i) \sim N(0, \sum)$. Here, "$\sum$" stands for covariance matrix given by $\begin{pmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{21} & \sigma_{22} \end{pmatrix}$, in which σ_{ij} represents covariance components and σ_{11} is normalized to one for the model identification. Additionally, α and β are structural parameters, and $\mho_1$ and $\mho_2$ are matrices of reduced-form parameters. The order condition for the identification of the structural parameters requires that the column of x_{2i} should be greater than or equal to the column of y_{2i}. In our estimation, we suspected laser leveling (LASER) as an endogenous variable causing an endogeneity problem. We identified distance to equipment dealers (DSTED) as an instrumental variable and used it in the estimation process. This instrumental variable passed the relevancy and exclusion criteria.

3.2. Determinants of Acreage Allocation

Producers can use one or more available irrigation methods to irrigate their crops. $Y_m = (y_1, y_2, \ldots, y_M)$ is the fraction of irrigated area using M different irrigation methods. The value associated with each variable should be within the interval [0, 1]. Here the dependent variables associated with areas under a particular irrigation technology are the fraction of the whole farmland area. We cannot use a probit or logit model as it does not allow a fractional value as a dependent variable. To deal with this type of problem, we use a nonlinear function that satisfies $0 \leq g(.) \leq 1$, in which $g(.)$ is a nonlinear model proposed by Papke and Wooldridge [29]. The conditional mean of the univariate dependent variable is given by $E(y|x) = g(x\beta)$, where x and β are the vectors of explanatory variables and parameters, respectively. A fractional model with Bernoulli distribution can be specified with the logistic link, and parameters can be estimated by maximizing the Bernoulli log-likelihood function. Recent papers by Mullahy [30], Murteira and Ramalho [31], and Paudel et al. [32] have discussed fractional multivariate estimation procedures. For the estimation process, we adopt a multivariate fractional regression method in which logit specification can be expressed as:

$$G_m = \frac{\exp(x'_m\beta)}{\sum_{i=1}^{M}\exp(x'_l\beta)},\ \text{with}\ \ m = 1\ldots\ldots M. \tag{4}$$

where x and β are independent variables and parameters, respectively, $G_m = G_m(X, \beta)$, conditional mean $0 < G_m < 1$ for all m, and $\sum_m^M G_m = 1$. Each crop producer v may irrigate using one or more available irrigation technologies. The contribution of each crop producer v to the log-likelihood can be expressed as:

$$logL_v(\beta) = \sum_{m=1}^{M} Y_{vm}logG_{vm} = \sum_{m=1}^{M-1} Y_{vm}log\frac{G_{vm}}{G_{vM}} + logG_{vM}. \tag{5}$$

where Y_{im} is the fraction of irrigated acreage under the $m\ th$ irrigation method and $G_{vM} = 1 - \sum_{m=1}^{M-1} G_{vm}$. Then, the quasi-maximum likelihood estimator is estimated by maximizing the log-likelihood of all crop producers N using the expression:

$$LL(\beta) = \sum_{v=1}^{N} logL_v\ (\beta) \tag{6}$$

where the estimated parameter β is consistent and asymptotically normal regardless of the true conditional distribution y, provided that G is correctly specified.

Employing the multivariate fractional regression method, our model estimation focused on fractions of acres devoted to flood, furrow, and center-pivot irrigation systems, alongside non-irrigated cropland acreage. The independent variables encompassed various facets, including sociodemographic data, input costs, risk attitudes, extension services utilization, and sources of information for production. This comprehensive approach enables a nuanced understanding of the factors influencing irrigation system choices and non-irrigated cropland acreage in our analysis.

4. Results and Discussion

4.1. Determinants of Irrigation Technology Adoption

Initially, we use a probit model to estimate the determinants of irrigation technology adoption in soybean and corn production. Estimated coefficients and marginal effects are presented in Appendix A, Table A1. Laser leveling is directly related to furrow irrigation, and the Natural Resources Conservation Service (NRCS) provides financial support for laser leveling. We suspect that this variable could be endogenous. To address this potential problem, the variable representing the distance to equipment dealer (DISTEQP) is used as an instrumental variable. Farmers physically close to the equipment dealer receive more information regarding laser leveling and are thus more likely to implement laser leveling. The distance to equipment dealer has nothing to do with the adoption of furrow irrigation. Its direct effect comes only through laser leveling. It is widely accepted that the exclusion restriction needs to be satisfied for an instrument to be valid. However, we do not have a formal statistical test of the exclusion restriction. Stock et al. [33] suggest that the F statistic should exceed 10 in the first-stage regression to be reliable for one endogenous regressor. We test whether we could treat laser leveling as an exogenous variable using the "*estat endogenous*" code in Stata 15 software. It provides Durbin and Wu–Hausman test statistics. The null hypothesis of the Durbin and Wu–Hausman tests is that the variable under consideration can be treated as exogenous. We find both test statistics highly significant, so we reject the null of exogeneity. Furthermore, Table A2 displays the estimated results of the first stage regression that justify the appropriateness of the instrumental variable. The first-stage results show that the instrumental variable is highly significant, the F-value is above 10, and the t-value is above 4. We also regress laser leveling directly to the dependent variable and find it nonsignificant. Furthermore, the Wald test for exogeneity of the instrumental variables has a chi-square value of 5.6 with a p-value of 0.01. All these statistics indicate that the instrument is not weak, and thus the distance to equipment dealer is a reasonable instrumental variable in this case.

Estimated coefficients using the IV-probit method are presented in Table 2. These coefficients are useful in explaining the impact direction of explanatory variables related to irrigation technology adoption (positive or negative impact). For example, the education of the farmer (EDU), his risk aversion attitude (RISKD2), and extension services as a source of information (EXT) are negatively associated with furrow irrigation technology adoption in soybean production. On the other hand, energy cost (ENGC), neighbor as a source of information (NBR), laser leveling (LASER), landholding (ACRE), and rental status (RENT) are positively associated with furrow irrigation adoption. Marginal effect values have better explanatory power than the estimated coefficients in a discrete choice model. We use marginal values presented in Table 2 (column 2) for a better explanation.

Table 2. Estimated results obtained from using an IV-probit model (irrigation technology adoption).

Dep. Variable	Soybean Irrigation Technology	
Furrow Irri. and Other (1,0)	**Coefficient**	**Marginal Effect**
EDU	-0.447 **	-0.4560 **
	(0.231)	(0.242)
ENGC	1.40×10^{-06}	-3.40×10^{-07}
	(1.07×10^{-05})	(1.10×10^{-05})
EXT	-0.165	-0.1648
	(0.284)	(0.2841)
NBR	0.0949	0.0878
	(0.254)	(0.260)
LASER	2.149 ***	2.1280 ***
	(0.267)	(0.260)
ACRE	1.14×10^{-04} *	0.00012 *
	(7.5×10^{-05})	(0.00007)
RENT	0.116	0.1160
	(0.306)	(0.3060)
RISKD2	-0.241	-0.2414
	(0.319)	(0.3180)
Observation	162	

Notes: EDU is a dummy variable representing an educational attainment of a college degree or above and below college degree (1, 0). Standard errors are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

From Table 2, furrow irrigation adoption is significantly affected by educational attainment, laser leveling, and landholding. Marginal effect values obtained from the IV-probit method are higher than those obtained from the probit method. On average, the expected probability of furrow irrigation adoption by farmers with a college degree or higher is 45% lower than farmers with education below the college degree. The potential reason could be that educated farmers might have evaluated the long-run benefit of water-conserving irrigation technologies with lower operational costs. Indeed, furrow irrigation systems might be expensive due to the higher costs of laser leveling. Our findings are similar to those of Toma et al. [34]. They state that education influences both behavior and intentions indirectly through profit orientation and the perceived usefulness of the information source. Education and information access were among the factors influencing multiple technology adoption. Educated farmers are more likely to access useful information to adopt a new technology in their farming practices. An increase in one acre of landholding increases the expected probability of furrow irrigation adoption by less than 1%. Compared to farms without laser leveling, furrow irrigation adoption is significantly affected by laser leveling. However, the impact of laser leveling on furrow irrigation adoption is higher than that found in the probit estimation. The estimated coefficients of other variables are not significant but are correctly signed. For example, the marginal effect of extension is -0.16, which indicates that the farmers who have access to extension services are 16% less likely to adopt furrow irrigation than farmers who do not have access to an extension service. This implies that strengthening extension services could have effective policy implications for water conservation efforts, irrigation productivity, and sustainability. Laser leveling makes the furrow irrigation system costly, but it also increases irrigation efficiency. Furrow irrigation is also a labor-intensive system.

4.2. Acreage Allocation

In this estimation, the dependent variables are the fractions of acres of cropland under flood, furrow, center-pivot irrigation systems, and the non-irrigated cropland. We suspected an endogeneity problem caused by the laser leveling variable in the technology adoption estimation and used an IV-probit method to estimate the impact. However, in multivariate fractional regression, we do not have a built-in option to use IV regression. To address the problem, the predicted value is obtained by regressing laser leveling on the distance to equipment dealer variable and then using the predicted value "ELASER" as an explanatory variable that acts as an instrumental variable in the multivariate fractional regression. The standard error may not be correct; however, regression results with an instrumental variable provide efficient estimates [35]. Table 3 displays the estimated marginal effect, considering a fraction of the non-irrigated farm as the base category. Marginal effect values have a better explanatory power than model coefficients in the fractional regression case.

Table 3. Marginal effects for acreage allocation as obtained from using a multivariate fractional regression model.

Variable	Marginal Effect	Marginal Effect	Marginal Effect	Marginal Effect
	Flood	**Furrow**	**Center-Pivot**	**No Irrigation**
EDU	0.0292	−0.0393	−0.0709 **	0.0809
	(0.0491)	(0.0687)	(0.0319)	(0.0710)
FARMREV	−0.0237 *	0.0339 *	0.0035	−0.0137
	(0.0139)	(0.0179)	(0.0088)	(0.0201)
RISKD2	0.0815 *	−0.2964 ***	−0.0440	0.2588 ***
	(0.0501)	(0.0837)	(0.0521)	(0.0770)
RISKD3	0.0623	−0.2861 ***	−0.0603 *	0.2841 ***
	(0.053)	(0.0821)	(0.0472)	(0.0769)
EXT	0.0736	0.0925	0.0278	−0.1940 ***
	(0.0525)	(0.0626)	(0.0331)	(0.0644)
NBR	0.0381	−0.0622	0.0253	−0.0012
	(0.0422)	(0.0663)	(0.0296)	(0.0647)
ELASER	−0.0118	1.0593 ***	−0.2098 *	−0.8376 ***
	(0.2264)	(0.2838)	(0.1169)	(0.3125)
EXPNC	−0.0037 **	0.0037	0.0020	−0.0020
	(0.0017)	(0.0027)	(0.0017)	(0.0028)
EDSP	0.0481 **	0.0212	0.0025	−0.0719 ***
	(0.0191)	(0.0272)	(0.0122)	(0.0277)
ACRE	−0.000007	−0.00004 ***	0.00002 ***	0.00002
	(0.00001)	(0.00002)	(0.00002)	(0.000015)
RENT	−0.1147 ***	0.2288 ***	−0.0140	0.0703
	(0.0429)	(0.0609)	(0.0286)	(0.0772)
Observation	119	119	119	119

Notes: ELASER is the predicted value of laser leveling choice by farmers obtained from regressing laser leveling on the distance to equipment dealer variable. Standard errors are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3 shows that the marginal effect of education for center-pivot acreage allocation is negative 0.079, which indicates that farmers with some college education allocate 7% less land to center-pivot-irrigated acreage than farmers having education below some college. The possible reason might be that more highly educated farmers may seek technologies different from the center-pivot method. Additionally, they might be interested in adopting surge valves, flow meters, or moisture/soil sensors to increase irrigation efficiency in their current irrigation systems. In particular, valve meters are devices that measure and regulate water flow; surge flows refer to sudden and temporary increases or fluctuations in water flow within a pipeline; and a sensor meter is an instrument equipped with sensors to measure specific physical or environmental parameters, providing data for monitoring moisture level in the farm. They may also seek information from the NRCS or other federal and state agencies. Higher education reduces furrow-irrigated acreage allocation as it is negatively signed, but it is not significant. Risk-averse farmers tend to allocate 29% less land to furrow-irrigated acreage, 4% less to center-pivot-irrigated acreage, and 26% more to non-irrigated acreage than risk-loving farmers. Risk-neutral farmers tend to allocate 28% less land to furrow-irrigated acreage, 6% less to center-pivot-irrigated acreage, and 28% more to non-irrigated acreage than risk-loving farmers. Regarding irrigation information, farmers utilizing extension services tend to allocate 19% less land to non-irrigated acreage than farmers utilizing no extension services. A reduced land allocation to non-irrigation shows the importance of extension services in irrigation efficiency, water productivity, and farm yield issues.

Regarding farming experience, one more year of farm experience tends to reduce the flood-irrigated acreage by less than 1%, implying that farming experience tends to favor an efficient irrigation technology over an inefficient furrow irrigation system. Landholding tends to reduce furrow irrigated acreage and increases the use of center-pivot acreage. Farmers with more land receive higher incomes and invest in an efficient irrigation technology. Similarly, farmers using rented land tend to allocate 20% more furrow irrigated land than producers farming their owned land. However, rental farm operators tend to allocate less acreage to center-pivot irrigation. The marginal effect value of “ELASER” is significant at 1%, 10%, and 5% for furrow acreage, center-pivot acreage, and non-irrigated acreage, respectively. The predicted value of laser leveling tends to increase the furrow-irrigated acreage significantly while reducing the center-pivot acreage and non-irrigated acreage. This finding is consistent with the values obtained in determinants of irrigation technology adoption estimation.

Our sample response indicates that furrow irrigation is Louisiana’s commonly practiced irrigation method. We noted that many farmers have not used valve meters, surge flows, and sensor meters. in their current irrigation systems Even with furrow irrigation, it has been shown that the adoption of irrigation practices can help to minimize total water use per acre while still meeting crop moisture requirements [25]. In general, implementing valve meters, surge flows, and sensor meters within existing irrigation systems can optimize water use efficiency, contributing to water conservation. In this context, raising educational awareness specifically encouraging producers to adopt these tools would be relevant in sustainable water use. In both estimations (irrigation technology adoption and acreage allocation), education, risk attitude, land holding, and laser leveling seem to be the most influential factors. More highly educated farmers tend to adopt a center-pivot or an even more efficient irrigation system and minimize the use of an inefficient furrow irrigation system. Highly educated farmers are innovative and willing to find better production methods. Here, education reflects formal educational attainment in a direct sense. The policy implication arising from this study on the adoption of water-conserving irrigation technology suggests that producers with higher educational attainment are inclined to adopt more efficient irrigation technologies.

Regardless of the insignificant impact of extension service and neighbor on irrigation technology adoption and acreage allocation, we tried to estimate the models adding an interaction term consisting of the extension and neighbor variables, but the results were not significantly different. The climatic factor could have been an important determinant of irrigation technology adoption and acreage allocation under various irrigation technologies. However, this study did not consider this variable to be an influential determinant because the data collected are from almost similar climatic characteristics. Since this study has utilized pooled data from 2015 and 2016, year-specific characteristics could impact our results differently. We used a year dummy variable to determine such an impact. The estimated results using the year dummy did not produce significantly different values than those obtained without the year dummy, except for the minimal change in the intercept coefficient. Additionally, no producer responded in both years.

Water availability for irrigation has not been a significant concern in Louisiana until recently. The heightened urgency results from reduced groundwater levels, the presence of a cone of depression, and saltwater intrusion in some of the major aquifers in the state. As of 2018, 71.8 percent of the total Louisiana corn area and 42.8 percent of the entire soybean area were irrigated [36]. Farmers increasingly use irrigation as a risk management strategy in crop production in the state. Concerns related to aquifer health have motivated farmers and policymakers to adopt, suggest, and, in some cases, incentivize efficient irrigation technology adoption along with irrigation water management practices. The imperative for sustainable groundwater usage is underscored by numerous studies highlighting a significant decline in groundwater levels in the southeastern regions. For instance, we observed a noteworthy expansion in irrigated soybeans and corn acreage in Arkansas since 1985, adjacent to Louisiana, coupled with a substantial decline in groundwater levels [37].

5. Conclusions

The primary objective of this study was to determine the factors affecting irrigation technology adoption and acreage allocation for different irrigation technologies in Louisiana crop production. For this purpose, we conducted a statewide mail survey in 2015 and 2016 to collect information regarding irrigation practices and concerns among the producers in the state [38]. We used an IV-probit model to estimate the determinants of irrigation technology adoption. Our findings indicate that higher educational attainment tends to significantly diminish the adoption of the furrow irrigation system. Additionally, a multivariate fractional regression model was used to identify and evaluate the determinants of acreage allocation under various irrigation technologies in crop production. The results indicated that risk aversion and total land holdings negatively impacted acreage allocation to furrow irrigation. In contrast, farm revenue, rent status, and laser leveling positively impacted acreage allocation to furrow irrigation. Similarly, farm revenue, rent status, and extension services are likely to increase center-pivot acreage allocation.

The findings of this study should be beneficial to those who are concerned about water productivity and water resource conservation. The results could help formulate effective tools to promote the adoption of efficient irrigation technology in crop production. Farmers with higher levels of education are innovative in farming and willing to find better production methods. Here, education reflects formal educational attainment in a direct sense. Making farmers more educated (with a formal degree) is not under our control. Educating farmers about the application of various modern technologies needs to be emphasized. The implementation of the farmer field school program along with a reliable extension service could help in this direction as the combined approach is an innovative, participatory, and interactive model approach to educating farmers about various farm practices, crop management strategies, and the upscaling of new technologies. Other effective approaches are attracting more educated people to farming, making farming an agribusiness operation, and training farmers on better farming technology and marketing practices. The land grant university extension system is poised to consistently deliver impactful training initiatives, ensuring the dissemination of knowledge and expertise in efficient and advantageous irrigation practices, as well as fostering the awareness and adoption of appropriate and innovative production technologies. Many studies [13,14] have demonstrated the importance of extension services in technology adoption. It is also evident that trust in the institution, networking, and social capital influence technology adoption. Extension services can play a substantial role in building up social capital and networking—incentive payments for adopting efficient irrigation technology and allocating more crop acreage for water-efficient irrigation technology as it is observed that producers in Louisiana seem to be applying irrigation water excessively in agricultural production [39].

Our study has some limitations, including the small sample size and the lack of additional information on soil and topographical characteristics. Irrigation technology adoption decisions depend on many factors, such as soil characteristics and land slope, which are lacking in this study. Including these variables in the regression model would help to avoid omitted variable bias.

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Appendix A

Table A1. Estimated coefficients of factors affecting furrow irrigation technology adoption in soybean production as obtained from the probit models.

	Soybean Irrigation Technology	
Variable	**Coefficient**	**Marginal Effect**
EDU	−1.011 **	−0.231 ***
	(0.409)	(0.0882)
FARMREV	0.0142	0.00324
	(0.105)	(0.0239)
RISKD2	−1.297 ***	−0.292 ***
	(0.403)	(0.0804)
RISKD3	−0.913 **	−0.198 **
	(0.440)	(0.0906)
ENGC	1.35×10^{-05}	0.0000031
	(1.58×10^{-05})	(0.0000035)
EXT	0.465	0.106
	(0.299)	(0.0683)
NBR	0.635 **	0.145 **
	(0.323)	(0.0701)
DISTEQP	−0.0228	−0.00521
	(0.0196)	(0.00429)
LASER	0.685 **	0.156 **
	(0.328)	(0.0700)
EDSP	0.238	0.0543
	(0.150)	(0.0350)
ACRE	0.000247 *	0.0000565 **
	(0.00013)	(0.000030)
RENT	0.714 **	0.163 **
	(0.358)	(0.0803)
DISTOWN	−0.0373 *	−0.00853 *
	(0.0212)	(0.00490)
Constant	0.920	
	(1.160)	

Notes: Standard errors are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A2. Estimated first-stage results using the IV-probit model (furrow irrigation technology).

Variable	Soybean Irrigation
Laser Leveling	**First-Stage Coefficient**
EDU	0.221 ***
	(0.0829)
FARMREV	0.0294
	(0.0237)
RISKD2	−0.0409
	(0.0991)
ENERGYC	4.17×10^{-06} **
	(1.79×10^{-06})
NBR	0.0947
	(0.0817)
EXT	0.197 **
	(0.0844)
ACRE	-2.28×10^{-05}
	(2.68×10^{-05})
RENT	0.133
	(0.0933)
DISTEQP	−0.00813 **
	(0.00368)
Constant	0.216
	(0.287)

Notes: Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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