Adoption of Irrigation Technology and Best Management Practices under Climate Risks: Evidence from Arkansas, United States

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Abstract

Water shortage is likely intensified by climate change. Although advanced irrigation technologies and agricultural water management practices are widely promoted, farmers' adoption behavior is not well understood in the climate change context. This study helps fill this gap by assessing how climate risk affects such adoption. We construct moment-based climate risk measures that better reflect its volatility and extremes and apply them in multiple discrete choice modeling procedures. We also extend existing literature focusing solely on irrigation technologies to include conservation practices such as the Best Management Practices (BMPs), thereby providing a more complete picture of conservation practices. Jointly using the Arkansas subset of USDA Farm and Ranch Irrigation Survey and Census of Agriculture over years and multiple climate records, we find climate risk plays a role in the adoption of advanced irrigation technologies and BMPs, and suggest the policy relevance of the consideration of climate risk in understanding farmers' technology adoption.

Key words: irrigation technology, Best Management Practices (BMPs), adoption, climate risk

Introduction

Water shortage has deteriorated sharply in recent years and therefore becomes a major concern for policy makers and researchers. The irrigation agriculture, which accounts for the majority of consumptive water use in the United States, comes to the center of the water shortage conflict. As a result, advanced irrigation technologies which improve water efficiency, have been proposed as a solution and therefore intrigues numerous technology adoption studies. However, the adoption decision regarding more efficient water management practices, such as Best Management Practices (BMPs), have never been investigated. In fact, BMPs are probably the most widely suggested water management practices in the United States agriculture, which include irrigation scheduling, laser leveling, tailwater pits, alternative row irrigation, restricting runoff by diking end of field and irrigation scheduling services, and could play a substantial role in agricultural water conservation (Schaible and Aillery, 2012). However, the adoption rate remains low. This paradox needs to be well understood in the face of exacerbating water shortage, and rigorous investigation on such are therefore urgently required in search of in-depth policy implications.

Climate change, which appears as warming temperatures, fluctuating precipitation pattern and more extreme climate events, plays a profound role in irrigation agriculture. It not only worsens water shortage through reduced water supplies and increased water demands, but also potentially affect farmers' adoption decisions of both irrigation technologies and BMPs. There is an increasing literature assessing the impact of climate change on the adoption of advanced irrigation technologies (Negri and Brooks, 1990; Moreno and Sunding, 2005; Xie et al. 2014; Olen, Wu and Langpap, 2012). These studies generally employ the average precipitation and temperature as measurement of climate change. Such measures, however, are rather static and could not accurately capture the volatility of climate, or climate risk, which could increase over time. In fact, the reluctance of irrigation technology and BMP adoption can be potentially altered by climate risk. Hence, understanding the role climate risk plays in the adoption decisions of both irrigation technologies and BMPs is highly policy-relevant in deriving better welfare results for farm operators. To the best of our knowledge, there is no adoption study that takes into consideration BMP adoption in a climate change context.

This study helps fill these gaps by assessing how climate risk affects irrigation technology and BMP adoption. Our contribution is twofold. First, we extend existing literature focusing solely on irrigation technologies to include BMPs, thereby providing a more complete picture of agricultural water management. Second, we overcome the limits of most previous studies of using average temperature or precipitation that are insensitive to climate volatility by applying alternative climate risk indicators such as moment-based measures of predicted climate risk and counts of extreme weather events in recent climate history, and more comprehensively assess impacts of climate change.

Our empirical analysis is facilitated by the USDA Farm and Ranch Irrigation Survey and Census of Agriculture which covers the production years of 1988, 1994, 1998, 2003 and 2008, and climate statistics from multiple sources. We construct several climate risk measures and creatively incorporate them into discrete choice models where the adoption of irrigation technologies and BMPs are jointly modeled. Our empirical analysis takes two steps. First, we consider a binary choice of adoption of advanced irrigation technology (sprinkler) versus dis-adoption (gravity), which covers major crops in the state of Arkansas and should provide us a big picture of adoption. We further analyze the adoption decisions of irrigation technologies along with BMPs for irrigation. We find that the variance of climate measures generally discourages irrigation technology and BMP adoption. Such results are intuitive as increased climate volatility can degrade the effectiveness and efficiency of advanced irrigation technologies and increase difficulties in BMP application, which therefore appear less attractive to farmers. However, extreme events, as captured by the kurtosis of certain climate measures, are found to encourage adoption as BMP may potentially mitigate the economic loss associated with them.

The rest of our paper is organized as follows. The next section reviews relative literature on irrigation technology adoption and climate change. Empirical modeling strategy and data are then discussed in detail. Results from empirical estimation follow. We finally conclude with discussion over several policy implications that arise from our findings.

Literature review

Climate change receives increasing attention in economic literature. Hall, Stuntz, and Abrams (2008) demonstrates that climate change in the future will lead to higher temperature, more variability of precipitation, and high risk of drought. It is further shown that higher temperature reduces farm values in most seasons, while recent findings include the confirmed changes of agricultural profits due to shifting degree days and total precipitation in the growing season (Mendelsohn, Nordhaus and Shaw, 1994). Existing studies find impacts of climate change on different aspects of agricultural production (Mendelsohn, Nordhaus and Shaw, 1994; Brown and Rosenberg, 1999; Darwin, 1999; Dechenes and Greenstone, 2007). As a result, farmers are found to hedge against climate change through alternative crop choices (Xie et,al., 2014) , purchased damage-based insurances (Mishra and Goodwin, 2006) and weather derivatives (Musshoff, Odening and Xu, 2011; Kooten and Zhang, 2013). Interestingly, adoption of advanced irrigation technologies has received limited attention in literature. In fact, agricultural water use is substantially affected by climate change, and agricultural irrigation is therefore increasingly challenged due to both evaporation loss and growing demands of groundwater. Hence, farmers' adoption behavior in a climate change context needs to be well understood to assist policy decisions that aim to offset the negative impacts of climate change and help achieve the robustness of agricultural production.

Starting with the seminal paper of Ervin and Ervin (1982), existing studies have investigated how different factors affect irrigation technology adoption, which can be farm-specific, farmer-specific, technology-specific or institutional. Farm physical conditions such as soil permeability and texture are widely associated with irrigation technology adoption (Caswell and Zilberman, 1986; Negri and Brooks, 1990; Shrestha and Gopalakrishnan, 1993). Concerning farmer-specific factors, age and education are consistently linked with irrigation adoption decision (Koundouri et al., 2006; Olen et al., 2012). Technological traits are also investigated and are found relevant in farmers' choice among multiple available technologies (Moreno and Sunding, 2005). Moreover, existing studies further suggest institutional factors, such as land tenure, are found to play a role (Soule et al., 2000; Moreno and Sunding, 2005). Empirical analyses of adoption determinants in these studies are largely implemented through estimation of discrete choice models under the random utility framework (e.g. Negri and Brooks, 1990; Green and Sunding, 1997; Schoengold and Sunding, 2014).

A few studies do take into consideration climate risk factors as potential determinants of irrigation technology adoption, where total rainfall, the number of frost-free days and temperature are found to significantly influence the probability of adoption (Negri and Brooks, 1990; Olen, Wu and Langpap, 2012; Finkel and Nir, 1983; Schoengold and Sunding, 2014). Static climate indicators such as average temperature or precipitation are widely used. These measures, however, are insensitive to climate volatility which may increase over time. To capture such change, alternative and more capable climate risk measures are needed assessing its impacts in a reliable manner.

Almost all existing studies focus on irrigation technologies alone but not agricultural water management practices such as BMPs. In the real world, however, farmers are likely to adopt technologies and management strategies at the same time. In fact, BMPs are widely proved efficient in agricultural water management especially under scarcity (Negri and Hanchar, 1989; Waskom, 1994; Schaible and Aillery, 2012). Sophisticated water scheduling practices such as soil or plant moisture-sensing devices, commercial or government irrigation scheduling services, computer simulation models can help farmers decide when and how to irrigate and possibly reduce water use (Schaible and Aillery, 2012). Other practices such as laser leveling, tailwater pits, shortening of furrow length, alternate row irrigation, are designed to improve distributional uniformity and reuse water in farm irrigation system. Therefore, BMPs along with irrigdation technologies can enhance the adaptability of irrigated agriculture to climate change and offset its negative effects. Interestingly, like irrigation technology (Schaible and Aillery, 2012), most BMPs are not widely used by irrigators across the United States (Valentin, Bernardo, and Kastens, 2004). The reluctance of adoption can potentially result from production uncertainties associated with climate change. Such impacts need to be understood. This paper aims to bridge these gaps. To our knowledge, empirical assessments of the effect of climate risk on irrigation technology adoption, especially with consideration of BMPs, are limited, which should be the main focus of the current study.

Analytical strategy

We now model the adoption of irrigation technologies and BMPs in a climate change context. A farmer i is expected to make irrigation decision to maximize his/her expected utility, conditional on climate risk along with farm (physical), farmer (demographic) and institutional characteristics. To irrigation technologies are considered: traditional gravity irrigation versus sprinkler irrigation. Concerning technological traits, although sophisticated irrigation scheduling strategies can be considered as a subset of BMPs, they differ from other BMPs such as laser leveling and tailwater pits due to their capital-intensive nature. Moreover, BMPs as of their specific traits are mostly applied to gravity but not sprinkler irrigation (Schaible and Aillery, 2012). In light of such differences, we consider BMPs, narrowly defined, and scheduling as two sets of agricultural water management practices in the current analysis. Therefore, farmer i faces six alternatives (technology packages): 1) traditional gravity irrigation without BMPs or scheduling, 2) traditional gravity irrigation with BMPs but without scheduling, 3) traditional gravity irrigation without BMPs but with scheduling, 4) traditional gravity irrigation with both BMPs and water scheduling practices, 5) sprinkler without scheduling, and 6) sprinkler with scheduling.

Farmer i chooses to adopt a technology package j out of the alternative set n for crop k iff

(1) $$Y_{ik}^{*} \equiv E\left[U_{ikj}\right] - E[U_{ikn}] > 0, \quad \forall n \neq j$$

where U_{ikj} is the utility that farmer i derives from the application of technology package j for crop k, and Y_i^{*} denotes the unobservable random index for farmer i that represents his/her propensity to adopt technology package j. U_{ikj} is further assumed in a random utility framework to take the following function form:

(2) $$U_{ikj} = \beta_1 C_i + \beta_2 Z_{ik} + \beta_3 Y + \beta_4 CT_i + \epsilon_{ikj} \equiv V_{ikj} + \epsilon_{ikj}$$

where C_i is a vector of climate indicators; Z_{ik} controls for farm characteristics such as farm size, water scarcity and soil condition, demographic characteristics such as the age and main occupation of the farmer, and institutional factors such as land tenure; Y is a vector of year dummies to capture any macroeconomic dynamics that may affect irrigation adoption in a systematic manner; CT_i further controls for county fixed effects; and finally ϵ_{ikj} is the error term.

Among all coefficient estimates, β_1 is of our main interest which captures the effects of climate risk on the adoption behavior of farmer i. The measures of climate risk, C_i, or farmer i's beliefs of future climate conditions based on climate history, are worth further discussion. Recent studies suggest the use of moment-based measurement of productivity uncertainty that could better capture the volatility of subject under investigation (e.g. Koundouri et al., 2006). We incorporate such strategy into climate risk measurement and construct accordingly the first four moments, namely mean, variance, skewness and kurtosis of temperature and precipitation, based on historical records. Moreover, we also incorporate indicators of extreme climate events, such as harmful degree days and severe drought, to better reflect climate risk that could further affect farmer i's adoption decisions. On the other hand, covariates included in Z include: 1) age of the farmer, 2) a binary main occupation indicator suggesting if it is on-farm agricultural production or not, 3) farm size, 4) the number of crops the farmer cultivates, 5) the percentage of land rented or leased in from others, 6) two water scarcity measures that affect irrigation (the depth to the water in the lagged year, the percentage of groundwater use), 7) three binary indicators of soil type (clay, sand, silt) and a continuous measure of soil permeability.

Based on the random utility framework and decision rule as outlined in equations (1) and (2), we further formalize the adoption decision. Specifically, the probability for farmer i to choose technology package j for crop k can be expressed as:

$$(3) \qquad p_{ikj} = \Pr\left(U_{ikj} > U_{ikn}\right) = \Pr\left(\varepsilon_{ikn} < V_{ikj} - V_{ikn} + \varepsilon_{ikj}\right) = \frac{exp(V_{ikj})}{\sum_n exp(V_{ikn})},\ \forall n \neq j$$

where V_{ikj} is the determinative part of the random utility as defined in equation (2).

Our empirical analysis takes two steps. First, to parallel existing adoption studies on irrigation technologies alone, we consider a binary choice of advanced irrigation technology adoption (sprinkler) versus dis-adoption (gravity). Conditional logit models, accounting for year and county fixed effects, are estimated for corn and cotton, two major crops in Arkansas. Second, we further analyze the joint adoption decision of irrigation technologies along with BMPs: the six technology packages as discussed above. This is modeled in a multinomial logit environment and should further assist our understanding of technology-specific adoption determinants.

Data description

Our main data are extracted from USDA Farm and Ranch Irrigation Survey and Census of Agriculture which covers the production years of 1988, 1994, 1998, 2003 and 2008. It is a repeated cross-sectional household survey that totally presents 2,140 farm-level observations located in the state of Arkansas. This dataset provides detailed information about agricultural production patterns, physical characteristics of farms and socioeconomic characteristics of the farmers. Information on the adoption of advanced irrigation technologies and BMPs are also available on a crop-specific basis.

In addition to the USDA data, we also collect county-level climate data from secondary sources. The monthly precipitation, mean, min and max monthly temperatures are obtained from PRISM Climate Group (2014). Using these climate datasets, we are able to construct the four moments (mean, variance, skewness and kurtosis) of temperature and precipitation as climate risk measures. We further consider additional measures of climate risk, namely harmful degree days and severe drought. The degree days are a standard agronomic measure affecting plant growth, to which daily temperature are converted to measure cumulative exposure of crops to heat during the growing season (Hodges 1991; Grierson 2002; Deschenes and Greenstone, 2007). Harmful degree days, where high temperature are observed, are expected to influence the adoption of advanced irrigation technologies and BMPs. Specifically, it is suggested in literature that the temperature higher than 93.2^{0}F will be harmful to the crop (Ritchie and NeSmith, 1991; Deschenes and Greenstone, 2007). Empirically, we sum up all positive differences between daily average temperatures and the threshold of 93.2 ^{0}F over the entire cropping season (April 1 to September 30) and obtain harmful degree days as the total. Moreover, severe drought is considered as another climate risk measure. Computation is based on the NOAA-Dai database, provided by Earth system Research Laboratory PSD (2014). Specifically, we compute the Palmer Drought Severity Index

(PDSI) where a daily index below -3 is generally considered as severe drought (Palmer 1965; NIDIS, 2014). The indicator is then computed as the ratio of number of days of severe drought over total number of days in the cropping season. Finally, control for soil quality is facilitated by the USDA-NRCS Soil Survey (2014).

Table 1 reports summary statistics from USDA's FRIS and Census of Agriculture for the years of 1988, 1994, 1998, 2003 and 2008, and provides information of farm level variable mean and standard deviation. Annual number of farms included in the survey range from 244 and 567, and a total of 2,140 observations are presented. The annual adoption rate of BMPs ranges between 0.33 (in 1988) and 0.54 (in 1998). The adoption rate of scheduling practices is comparatively low, but roughly constant though with a small peak in 1994. Water depth ascends during period 1988 to 1998, and declines subsequently. This trajectory over time coincides with that of adoption of BMPs and irrigation scheduling, implying that water scarcity contributes to the adoption of those practices. Annual average temperature increases firstly, and reaches the peak in 1998, and then decreases consequently. The coincidence of the change of average temperature and farmers' adoption of BMPs and irrigation scheduling indicates the possibility of causal relationships among them. Finally, annual average precipitation fluctuates and shows little systematical trend.

Empirical results

Binary irrigation technology adoption: Sprinkler versus gravity

Table 2 reports conditional logit estimation results for corn and cotton, two major crops in the state of Arkansas. As previously discussed, climate risk is now measured by four constructed moments of precipitation and temperature as well as measures of extreme climate events concerning both harmful degree days and severe drought. Three specifications are estimated accordingly, each employing a different climate measures. In the first specification, as applied in model 1 and model 4 use short-, middle- and long-term extreme events as the measure of future climate risk. The second specification, as applied in model 2, alternatively uses the first four moments of mean temperature and precipitation distribution on a five year basis. Finally, specification 3 as applied in model 3 estimates the moments of climate distribution over longer period (ten years).

Our results show that climate risk does play a role in irrigation technology choice. In the corn model, farmers are less likely to adopt sprinkler with the increase of harmful degree days. This is probably due to the evaporative loss of irrigation water which makes sprinkler less effective. Such finding is in line with previous literature which suggests that a substantial portion (up to 15%) of irrigation water can evaporate in hot regions which makes farmers reluctant to adopt sprinklers (Finkel and Nir 1983). Moreover, only long-term harmful degree days is found of significant effect, possibly due to farmers' lagged response to heat. Interestingly, the harmful degree days is not significant for the adoption of sprinkler in the cotton model, which may be explained by the different agronomic features of cotton but is worth further investigation. In addition to harmful degree days, there is a significant linkage between sprinkler adoption decision and the skewness, or symmetry of temperature distribution. In particular, the skewness of temperature in last 5 (10) years significantly decreases the possibility of adoption of sprinkler for corn (cotton). Further analysis shows that the skewness of monthly average temperature is negative. That is, the higher value the skewness measure takes, the less frequency of extreme cold temperature would likely occur. As sprinklers are always used to protect crops from frozen in cold weather, the farmers exposed to fewer cold days may not need as much to employ sprinkler for protection and therefore may be more hesitate to adopt it. In contrast, our results generally show little systematic linkage between precipitation measures and sprinkler adoption.

Among the additional covariates, larger farms are generally more likely to adopt sprinkler than small farms, possibly due to the economy of scale. The corn model shows that full-time farmers are more likely to adopt sprinkler than part-time farmers, and that older farmers are less likely to adopt than younger ones. The cotton model suggests that adoption is negatively associated with crop diversity and the ratio of rented/leased land operated by that farmer. These associations, however, appear much less systematic as compared to those concerning climate risk measures. Therefore, failure to consider climate factors in irrigation technology modeling may not be able to yield the optimal policy results.

Crop-specific adoption of irrigation technology and best management practices

Estimated multinomial logit crop-specific technology and BMPs adoption models are reported in Table 3 and Table 4. As discussed above, there are six technology packages of irrigation technologies and practices. The gravity without scheduling or BMPs is the base group, and is therefore not reported. The rice model (Table 3) and soybean model (Table 4) use dissimilar specifications with different climate measures. We first employ conventional measures of climate change: annual mean temperature, annual precipitation and their squares, consistent with most irrigation technology adoption studies considering climate change (Olen, Wu and Langpap, 2012; Xie et al. 2011; Mendelsohn et al, 1994). The coefficients of the quadratic terms can be explained as the second-order impacts of climate on the irrigation decision (Schuck and Green 2001). Since climate risk is found to play a role in the farmer's adoption decision, we then extend our analysis by using rescaled four moments of climate distribution interacted with farm size, to analyze the influence of climate risk on the technology and BMPs adoption decision for soybean (Table 4).

The rice model estimates the quadratic relation between climate risk (e.g. temperature, precipitation) and the adoption of sprinkler. In contrast with the other technology adoption studies, our model provides more interesting and complete information about the climates determinants which affect not only sprinkler technology adoption, but also adoption of management practices. We find the quadratic relation between the temperature and the adoption of the sprinkler with scheduling. The negative coefficient of the squared temperature indicates that in hot regions sprinkler with scheduling is less likely to be adopted by farmers. It further reconfirms the influence of high temperature on evaporation and technology choice. Conversely, the temperature is found insignificantly affecting the adoption of BMPs when traditional gravity technology is used. These results provide the evidence that temperature plays a more important role in determining the adoption of sprinkler than the adoption of management practices. In addition to temperature, precipitation also nonlinearly affects the adoption of sprinkler, no matter it is combined adopted with irrigation scheduling practice or not. However, the coefficient signs of the squared precipitation in the sprinkler with and without scheduling models are opposite. In particular, the positive coefficient sign of squared precipitation in the adoption model of sprinkler without scheduling provides some evidence that in regions with more rainfall, sprinkler is favored because it has great control over the water quantity applied. In contrast, when scheduling is taken into account, extra rainfall discourages the adoption of sprinkler and scheduling. It is likely because the adoption of water-saving irrigation scheduling becomes less requisite in regions with enough rainfall. Therefore the negative effect of the precipitation on the adoption of scheduling offsets the positive effect on sprinkler adoption.

Our results of soybean model further highlights the important role of the climate risk in farmer's adoption decision of the combination of irrigation technologies, scheduling and other BMPs. The second moment of precipitation, which approximates the expected variance of the precipitation over last 10 years, is significant for the adoption of scheduling and other BMPs. The third moment, which approximates the skewness of precipitation distribution, is found to be negatively significant to the adoption of gravity irrigation with BMPs. The fourth moment of precipitation distribution, which approximates the extreme precipitation event, are found to be highly significant to the adoption of gravity with scheduling and the adoption of gravity with both BMPs and scheduling. These results indicate that the effect of four moments have varying effects on different technology packages. In particular, the greater the variance of the precipitation, the less probability that farmers decide to adopt gravity irrigation with BMPs and scheduling. This allows a farmer to avoid further loss of investment in the face of high climate risk. Moreover, the greater the skewness of the precipitation, the less the probability that farmers decide to adopt the BMPs. Since the precipitation distribution in Arkansas are skewed to the right, the water-saving BMPs are less necessary with excessive precipitation. Finally, the positive coefficient of the fourth moment indicates that extreme precipitation promotes the adoption of scheduling and other BMPs. This result provides evidence that farmers invest in BMPs to hedge against the extreme precipitation events, mainly in water shortage days.

Other coefficient estimates in our multinomial procedures with rice and soybean may provide some additional insights. Factors affect adoption of irrigation technologies and management practices are lined up in a crop-specific manner. In the rice model, the irrigation decision highly depends on crop diversity and the percentage use of the groundwater. Also, the crop diversity positively affects the adoption of the management practices when traditional gravity technology is applied. However, the percentage of the groundwater discourages the adoption of sprinkler with scheduling and the adoption of gravity with scheduling or other BMPs. Moreover, the lag variable of county-average water depth, which approximates water scarcity, prompts the adoption of water-saving sprinkler technology with scheduling. Finally, the soil permeability indicator, ksat, also encourages the adoption of sprinkler with scheduling and gravity with scheduling. This supports the view that sprinkler augments soil quality and irrigation scheduling conserves water. Compared to rice model, soybean model has similar significant determinants, but most of them shows different significance and magnitudes on the adoption of various technology and BMPs. Unlike rice, the interaction between farm size and farm size are found to be negatively significant in soybean model, which indicates that the larger farm size decreases the farmer's response to the soil quality. In general, these effects again appear to be much less systematic as compared to that of the climate indicators, especially precipitation, which significantly affects adoption of irrigation technologies and management practices.

Conclusion

In this article we use the crop-specific discrete choice models to estimate the farmer's adoption decision of advanced irrigation technology, scheduling practices and other BMPs responding to climate risk. We first apply conditional logit models to investigate how climate risk affects the probability of adoption concerning irrigation technologies alone in a binary choice setting (sprinkler versus gravity irrigation). We further analyze the joint adoption decisions of irrigation technologies along with scheduling practices and other BMPs through crop-specific multinomial logit procedures. It is generally found that climate risk plays a role in the adoption of advanced irrigation technologies and agricultural water management practices. Unsurprisingly, the magnitudes and statistical significance of such effects vary across crop types and depend on the nature of climate risk measures applied in certain contexts. While we do see consistent evidence that increasing climate volatility and more frequent occurrence of extreme climate events affect farmers' adoption decisions. Such effects are highly nonlinear, and therefore static climate risk measures may not accurately capture climate change. Hence, our study can serve as a baseline analysis on irrigation technology and management practice adoption which calls for further investigations.

Our findings lead to several policy implications. On the supply side, further research and development of irrigation technologies and BMPs should place more emphasis on the mitigation of climate impacts associated with its increasing volatility. Such improvements should be made available to farm operators in a cost-effective manner. On the demand side, knowledge of modern irrigation technologies and BMPs should be further developed. As a result, agricultural extension service therefore can never be overemphasized and should specifically focus on the spread of knowledge concerning the central role of advanced irrigation technologies and agricultural water management practices in a climate change context.

Table 1: Summary Statistics

	1988	1994	1998	2003	2008
BMP adoption	0.33 (0.47)	0.52 (0.50)	0.54 (0.50)	0.37 (0.48)	0.39 (0.49)
Scheduling adoption	0.10 (0.30)	0.12 (0.33)	0.10 (0.31)	0.08 (0.27)	0.09 (0.29)
Age	49.32 (13.57)	49.10 (12.35)	49.54 (12.42)	51.24 (12.54)	53.22 (12.71)
Depth	42.67 (39.45)	47.58 (45.51)	48.90 (42.13)	48.52 (36.31)	45.24 (27.55)
Groundwater ratio	0.93 (0.17)	0.94 (0.18)	0.87 (0.28)	0.83 (0.32)	0.85 (0.30)
Farm size	1760.42 (1890.2)	2095.74 (1947.04)	2095.74 (2203.83)	2040.64 (2016.79)	2386.12 (2223.75)
Crop diversity	1.89 (0.76)	1.70 (0.72)	1.79 (0.71)	1.76 (0.70)	1.80 (0.67)
Percentage of rent	0.69 (0.40)	0.72 (0.37)	0.75 (0.37)	0.74 (0.37)	0.74 (0.37)
Gender	0.98 (0.15)	0.98 (0.15)	0.98 (0.14)	0.98 (0.14)	0.97 (0.17)
Main profession	0.95 (0.22)	0.94 (0.23)	0.95 (0.22)	0.95 (0.22)	0.94 (0.25)
Average temperature	17.37 (1.68)	17.54 (1.67)	18.71 (1.51)	17.33 (1.79)	17.24 (1.92)
Average precipitation	116.98 (18.92)	122.43 (9.47)	117.38 (13.13)	118.34 (17.68)	130.61 (12.82)

Table 2 Estimation Results for Crop-Specific irrigation technology adoption

	Corn		Cotton	
	Model 1	Model 2	Model 3	Model 4
farm	14.761*** (0.957)	14.860***(1.035)	1.126 (0.735)	0.914 (0.72)
age	-0.022* (0.012)	-0.024** (0.012)	-0.011 (0.008)	-0.009 (0.007)
Farm size	0.001* (0.001)	0.001* (0.001)	0.001** (0.000)	0.001** (0.000)
Crop diversity	0.351 (0.288)	0.389 (0.285)	-0.397** (0.166)	-0.374** (0.168)
pt_rent	0.136 (0.477)	0.047 (0.496)	-1.080* (0.64)	-1.140* (0.64)
Lag of county mean depth	0.047 (0.034)	0.049 (0.033)	-0.001 (0.011)	0 (0.01)
Percentage of groundwater	1.361 (1.461)	1.313 (1.462)	0.051 (0.943)	0.159 (0.944)
Harmful degree days (5 years)	0 (0.003)			0.001 (0.003)
Harmful degree days (10 years)	0.006 (0.004)			0 (0.006)
Harmful degree days (30 years)	-0.008* (0.005)			-0.004 (0.004)
pt_sevdrought (5 years)	1.622 (8.67)			6.405 (6.07)
pt_sevdrought (10 years)	10.314 (26.684)			-14.334 (14.936)
pt_sevdrought (30 years)	22.187 (59.735)			19.551 (39.031)
ksat_farmsize	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
clay_farmsize	0.000 (0.000)	0.000 (0.000)	-0.000***(0.000)	-0.000**(0.000)
sand_farmsize	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Year dummies	Yes	Yes	Yes	Yes
Temperature mean (5 years)		2.801 (2.567)		
Temperature sd (5 years)		-0.728 (4.845)		
Temperature skewness (5 years)		-55.711** (22.237)		
Temperature kurtosis (5 years)		-21.813 (29.9)		
Precipitation mean (5 years)		-0.036 (0.103)		
Precipitation sd (5 years)		-0.01 (0.084)		
Precipitation skewness (5 years)		-2.018 (2.407)		
Precipitation kurtosis (5 years)		0.455 (0.578)		
Temperature mean (10 years)			-0.928 (2.577)	
Temperature sd (10 years)			3.577 (6.896)	
Temperature skewness (10 years)			-82.877* (47.133)	
Temperature kurtosis (10 years)			-32.772 (21.851)	
Precipitation mean (10 years)			-0.072 (0.181)	
Precipitation sd (10 years)			0.109 (0.236)	

Precipitation skewness (10 years)			2.27 (4.424)	
Precipitation kurtosis (10 years)			-0.475 (0.594)	
N	333	333	475	475

Notes: Standard errors in parentheses. *significant at 10%; **significant at 5%, ***significant at 1%.

Table 3 Estimation Results for irrigation technology and management practices adoption for rice (n=1,525)

	Gravity with BMP	Gravity with scheduling	Gravity with BMP and scheduling	Sprinkler without scheduling	Sprinkler with scheduling
farm	0.396 (0.337)	0.131 (0.607)	1.058 (0.688)	18.707 .	14.922 .
age	0.001(0.006)	-0.01 (0.010)	-0.012* (0.007)	-0.002 (0.025)	0.044 (0.042)
Farm size	0.000 (0.000)	0.000 (0.000)	0 0.000	0 0.000	-0.018 (0.000)
Crop diversity	0.345*** (0.128)	0.871*** (0.298)	0.630*** (0.212)	0.374 (0.692)	0.95 (1.485)
Lag of county mean depth	-0.01 (0.010)	-0.007 (0.019)	-0.008 (0.021)	-0.036 (0.053)	2.470*** (0.047)
Percentage of groundwater	-0.965** (0.397)	-0.264 (0.544)	-1.401*** (0.342)	9.228* (5.102)	-16.917* (9.658)
ksat	0.049 (0.035)	1.064*** (0.079)	0.043 (0.049)	3.287** (1.473)	7.560*** (0.162)
clay	-0.03 (0.039)	-0.086 (0.096)	-0.115 (0.080)	1.365 (1.135)	5.603 .
sand	-0.094 (0.061)	-1.175*** (0.156)	-0.108 (0.097)	-2.654 (2.396)	-9.379 0.000
Percentage of rent	-0.07 (0.213)	0.258 (0.357)	-0.116 (0.317)	0.709 (1.113)	-12.038 (8.585)
Ksat*farmsize	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.001 (0.001)
Clay*farmsize	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000*** (0.000)
Sand*farmsize	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.001)
year dummies	yes	yes	yes	yes	yes
County dummies	yes	yes	yes	yes	yes
temperature	-1.95 (2.582)	-4.743 (3.539)	3.329 (3.102)	-1.248 (10.512)	230.712 .
temperature squared	0.065 (0.079)	0.103 (0.126)	-0.137 (0.109)	0.061 (0.369)	-4.205*** (0.038)
precipitation	-0.044 (0.118)	-0.28 (0.190)	0.005 (0.192)	-2.076** (0.989)	20.483 .
Precipitation squared	0 (0.001)	0.001 (0.001)	0 (0.001)	0.010** (0.005)	-0.120*** (0.001)
_cons	18.213 (27.036)	(32.462) (32.462)	-13.895 (26.485)	5.64 .	-3788.65 0.000

Notes: Standard errors in parentheses. *significant at 10%; **significant at 5%, ***significant at 1%.

Table 4 Estimation Results for irrigation technology and management practices adoption for soybean

	Gravity with BMP	Gravity with scheduling	Gravity with BMP and scheduling	Sprinkler without scheduling	Sprinkler with scheduling
farm	0.32 (0.390)	0.045 (0.591)	0.197 (0.544)	0.369 (0.479)	17.134*** (1.259)
experience	0.006 (0.005)	-0.007 (0.010)	-0.008 (0.007)	0.001 (0.010)	0.000 (0.010)
farmsize	-0.006 (0.006)	-0.008 (0.012)	-0.006 (0.014)	0.008 (0.008)	0.008 (0.011)
Crop diversity	0.484*** (0.124)	0.790* (0.405)	0.278 (0.311)	0.502 (0.311)	0.454 (0.463)
Lag of county mean depth	0.001 (0.005)	-0.012 (0.016)	0.006 (0.022)	-0.009 (0.006)	-0.015 (0.011)
Percentage of groundwater	-0.916*** (0.320)	0.277 (0.779)	-1.501** (0.600)	0.374 (0.641)	-0.629 (0.912)
ksat	-0.014 (0.016)	-0.02 (0.032)	0.014 (0.043)	0.116*** (0.024)	0.071*** (0.025)
Percentage of rent	-0.065 (0.208)	0.504 (0.389)	0.226 (0.388)	-0.426 (0.282)	-0.127 (0.512)
ksat_farmsize	-0.000** (0.000)	0.000 (0.000)	0.000 (0.000)	-0.000*** 0.000	-0.000*** 0.000
year dummies	yes	yes	yes	yes	yes
county dummies	yes	yes	yes	yes	yes
Farmsize*temperature mean (10 years)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Farmsize* temperature SD (10 years)	0.000 (0.000)	0.000 (0.001)	0.000 (0.001)	-0.001 (0.001)	0.000 (0.001)
Farmsize*temperature Skewness (10 years)	0.000 (0.003)	0.002 (0.008)	-0.004 (0.006)	-0.004 (0.005)	-0.006 (0.007)
Farmsize* temperature Kurtosis (10 years)	0.003 (0.002)	0.004 (0.005)	0.002 (0.004)	0.002 (0.002)	-0.003 (0.005)
Farmsize* precipitation mean (10 years)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Farmsize*precipitation SD (10 years)	0.000 (0.000)	0.000 (0.000)	-0.000* (0.000)	0.000 (0.000)	0.000 (0.000)
farmsize*precipitation skewness (10 years)	-0.001** (0.001)	-0.002 (0.001)	-0.001* (0.001)	-0.001 (0.001)	0.000 (0.001)
farmsize*precipitation kurtosis (10 years)	0.000* (0.000)	0.000* (0.000)	0.000*** (0.000)	0.000 (0.000)	0.000 (0.000)
_cons	-1.270* (0.722)	-3.366* (1.942)	-1.545 (1.867)	-2.142 (1.424)	-17.549 (0.000)

Notes: Standard errors in parentheses. *significant at 10%; **significant at 5%, ***significant at 1%.

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