Journal of Hydrology 552 (2017) 81–91

Contents lists available at ScienceDirect

Journal of Hydrology

journal homepage: www.elsevier.com/locate/jhydrol

Research papers

Do climate factors matter for producers' irrigation practices decisions?

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ARTICLE INFO

Article history:
Received 28 March 2017
Received in revised form 23 May 2017
Accepted 22 June 2017
Available online 26 June 2017
This manuscript was handled by Geoff Syme, Editor-in-Chief, with the assistance of Hazi Mohammad Azamathulla, Associate Editor

JEL Codes:
Q25
Q12

Keywords:
Drought
Intensive precipitation
Climate
Irrigation technology
Water Management Practices

ABSTRACT

The study examines whether climatic factors play a role in producers' irrigation decisions. Empirical analysis uses a set of repeated cross-sectional farm level data collected in three American states: Arkansas, Mississippi, and Louisiana. Empirical findings provide evidence that climatic conditions are factored into irrigation decisions. For example, higher mean temperature reduces the likelihood of using sprinkler irrigation in the study area. More importantly, findings of this study point to the importance of studying both long-term and short-term climate patterns. Long-term climate patterns weigh more in producers' decisions regarding the use of sprinklers. Both long-term and short-term climate patterns seem to affect producers' decisions on the use of WMPs. Producers may respond differently to similar changes in long-term and short-term climate patterns. For example, a higher occurrence of drought in the previous year predicts a higher rate of sprinklers, while an increasing trend of drought occurrence during the previous 30 years predicts the opposite. Our findings also highlight the importance of considering various aspects of the climate patterns. Average climate conditions, such as mean temperature and annual precipitation, and the occurrences of extreme weather events, such as droughts and intensive precipitation, have stronger predictive powers of producers' irrigation decisions than the coefficients of variation. In the study area, the occurrence of intensive precipitation seems to have the strongest impact on producers' irrigation decisions.

1. Introduction

Water shortage is a problem faced by agricultural producers throughout the world. To provide context, agricultural irrigation is responsible for nearly 80% of the total water use in the United States (Aillery and Schaible, 2016). The adoption of more efficient irrigation technology is a frequently proposed solution. Existing studies have identified a wide range of factors that may influence the adoption of more efficient technology. These factors include economic and institutional factors, farm and producer characteristics, and technology traits (Carey and Zilberman, 2002; Caswell and Zilberman, 1986; Koundouri et al., 2006; Moreno and Sunding, 2005).

Despite the wide variety of potential impacts of climate change on agricultural production, limited attention has been directed toward climatic factors and their effects on producers' irrigation decisions. Temperature and precipitation changes may impact the quantity of irrigation water applied and the timing of irrigations, in addition to the supply of water available for irrigation (Elliott et al., 2014; Frieler et al., 2014; Schlenker et al., 2007). Climate change will likely result in more variations in rainfall and temperature as well as more droughts and floods (Hall et al., 2008; Rosegrant et al., 2014). Irrigation is one of the main strategies that can reduce the exposure of producers to growing climate risks. Thus, it is important to consider the impact of climatic conditions on producers' irrigation decisions (Joyce et al., 2011).

The main focus of this research is to examine whether climatic factors play a role in producers' irrigation decisions. This study adds to a relatively small literature that links irrigation decisions and climatic factors (e.g., Frisvold and Deva, 2013; Huang et al., 2017; Negri et al., 2005; Olen et al., 2015). Specifically, this study makes two significant contributions. First, this study is among the very few that examines how climate information factors into producers' irrigation decisions. Multiple aspects of climate conditions are considered in the study including average temperature and precipitation, variations in these factors and the occurrence of extreme weather events. More importantly, climate variables are constructed using different lengths of previous periods to see which period is more likely to be factored into producers' decision making. When studying producers' irrigation behavior, one of the most relevant questions may be the time frame they use to consider changes in climatic conditions. Longer time periods may

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http://dx.doi.org/10.1016/j.jhydrol.2017.06.037
0022-1694/© 2017 Published by Elsevier B.V.

better capture long-term climate trends by smoothing out short term fluctuations. More recent weather events may exert larger impacts on producers who may only look to the recent past when making decisions. Despite the large body of literature on climate change, there is no uniform length of time used to measure climate variations. The length of 30 years is used in many previous studies that examine the impact of or adaptations to climate change. For example, Burke and Emerick (2006) measure long-run trends in climate over the period 1980–2000 and examine adaptation to climate change in U.S. agriculture. However, longer or shorter periods have also been employed. For example, to gauge producers' perceptions of climate change, Di Falco et al. (2011) use a survey question that asks whether producers have noticed changes in mean temperature and rainfall over the last two decades. To our knowledge, very few studies have examined which length of time producers have used in making their irrigation decisions.

Second, this study includes a larger set of irrigation decisions that may be influenced by climatic factors. Except for Huang et al. (2017), most studies to date have focused exclusively on the choices of irrigation technologies (e.g., sprinkler or drip irrigation versus flood irrigation). The exclusive attention to more efficient technologies neglects other actions farmers may undertake in response to a shrinking and more volatile water supply. This study analyzes the joint choices of more efficient irrigation technologies as well as Water Management Practices (WMPs). A wide variety of WMPs can reduce on-farm water use by improving the performance of existing irrigation systems (Negri and Hanchar, 1989; Waskom, 1994; Aillery and Schaible, 2016). Some WMPs may be better at addressing irrigation challenges brought on by more volatile weather patterns. For example, in the United States, tailwater recovery pits, often in conjunction with on-farm reservoirs, capture rainfall and irrigation runoff and store it to meet future irrigation needs (Negri and Brooks, 1990). The large initial capital requirement of sprinkler or drip irrigations makes those technologies unaffordable to poor producers. Therefore, the inclusion of WMPs is more relevant in less developed countries where producers are more vulnerable to climate risks (Brouwer, 2007) and are more likely to resort to WMPs.

The rest of the paper is organized as follows. The second section presents the empirical method. The third section describes the study area and the data sets used. The fourth section regression results. The fifth section concludes. It should be noted that although the study site is in a developed country, the approach used is not specific to the study area and can be readily applied to other areas as long as data are available.

2. Empirical method

Producers' decisions regarding irrigation technologies and/or WMPs can be modeled either as a set of binary variables (whether a technology and/or a WMP is used), or a set of continuous variables (share of a producer's crop land allocated to a technology and/or a WMP). The information available in the data will dictate whether binary or continuous variables are modeled. In the continuous case, the relationship between a producer's irrigation practice decisions and potential influencing factors can be expressed as:

$$y_{icjkt} = \boldsymbol{\alpha}_{cjk} + \mathbf{W}_{ict}\boldsymbol{\gamma}_{jk} + \mathrm{X}_{ict}\boldsymbol{\beta}_{jk} + \varepsilon_{icjkt} \tag{1}$$

In Eq. (1), the dependent variable y_{icjkt} is the share of producer i's farm land irrigated with technology j and/or WMP k in period t. Producer i is located in county c. The vectors $\boldsymbol{\beta}_{jk}$, and $\boldsymbol{\gamma}_{jk}$ are the parameters to be estimated and ε_{icjkt} is the error term in regressions. For each combination of technology j and WMP k, there will be an estimating equation. So multiple equations are estimated since there is usually more than one combination of technology j and WMP k. Eq. (1) is the general representation of all the estimating equations. It can be applied to any study area and any combination of different irrigation technologies and WMPs.

On the right-hand side, the key variables of interest are contained in the vector $\mathbf{W}_{ict}$, which measures historical climatic conditions that producers may use to form their irrigation decisions. Three sets of climate variables are included. First, the first set of variables measure the average climate conditions such as mean daily temperature (MDT) and total precipitation during the growing season. The second set of variables use variance to measure the volatility in temperature and precipitation. Coefficient of variation, instead of variance, is used so that the measure is unit free. Coefficient of variation (CV) is the ratio of the standard deviation to the mean. CV is not calculated for measures from the previous year since only one observation is used to construct such measures. The third set of variables gauge the occurrence of specific extreme events. The first even considered is drought. Computation of the drought variable is based on the Palmer Drought Severity Index, where a month of severe drought receives an index score of -3 or less (Palmer, 1965; NIDIS, 2016). Months during the growing season when severe drought occurs are used to construct the variable as the share of months experiencing severe drought. The second event considered is intensive rainfall. Negri et al. (2005) and Groisman et al. (2012) argue that daily precipitation more than 25.4 mm (one inch) is detrimental to crop growth. Therefore, we use the share of days in the growing season when precipitation exceeds 25.4 mm to measure the frequency of excessive precipitation events (Bell et al., 2004). Because large farms have larger exposure to climate risks than smaller farms, all climate variables are interacted with farm size.

To determine whether more recent or long-term temperature and precipitation patterns are better predictors of producers' irrigation decisions, the climate variables can be constructed using various lengths of previous periods. From the producers' point of view, it is reasonable to treat 30 years as a long-run time horizon. It is also possible that some producers may only look at what just happened in the previous year. Other lengths of time periods (e.g., previous 5 years, previous 10 years) can also be used. Variables that measure weather condition of the current year are not included because producers most likely have made decisions regarding irrigation technologies/WMPs prior to the irrigation season and before such information is observed.

When estimating Eq. (1), it is important to control for non-climate factors that may influence producers' decisions regarding irrigation technologies and/or WMPs. Those factors are included in the vector $\mathbf{X}_{ict}$. Findings from previous studies provide guidance on which variables to include in $\mathbf{X}_{ict}$. Economic factors, like input, crop, and water prices, impact technology choice, while institutional factors, such as land tenure, may also play a role (Soule et al., 2000; Moreno and Sunding, 2005). Installation costs and technological traits will also impact a producer's choice between available technologies (Moreno and Sunding, 2005; Koundouri et al., 2006; Olen et al., 2015). Farm size and land quality have also been shown to impact adoption (Caswell and Zilberman, 1986; Negri and Brooks, 1990; Shrestha and Gopalakrishnan, 1993). Similarly, producer characteristics, such as age and education, are often linked with irrigation decisions (Koundouri et al., 2006; Olen et al., 2015).

Since the dependent variable in Eq. (1) is continuous, county-level fixed effects can be used to control for any unobserved time-invariant county characteristics in estimating Eq. (1). Some important county-level factors include the characteristics of irrigation supply (e.g., water yields in the aquifer in groundwater using areas) and status of irrigation technology and WMPs development. In equation (1), the use of county-level fixed effects is denoted by the term, $\boldsymbol{\alpha}_{cjk}$. It captures any time-invariant county-level characteristics. A short explanation of the county-level fixed effects model is as follows. Lagging Eq. (1) by one time period generates Eq. (1a):

$$y_{icjk,t-1} = \boldsymbol{\alpha}_{cjk} + \mathbf{W}_{ic,t-1}\gamma_{jk} + \mathbf{X}_{ic,t-1}\boldsymbol{\beta}_{jk} + \varepsilon_{icjk,t-1}. \tag{1a}$$

Notice the lagged term of $\boldsymbol{\alpha}_{cjk}$ is itself because it is time invariant. Subtracting Eq. (1a) from (1) generates Eq. (1b):

$$(y_{icjkt} - y_{icjk,t-1}) = (\mathbf{W}_{ict} - \mathbf{W}_{ic,t-1})\gamma_{jk} + (\mathbf{X}_{ict} - \mathbf{X}_{ic,t-1})\boldsymbol{\beta}_{jk} + (\varepsilon_{icjkt} - \varepsilon_{icjk,t-1}). \tag{1b}$$

The term $\boldsymbol{\alpha}_{cjk}$ disappears in equation (1b). Estimating Eq. (1b) thus generates consistent estimates of all parameters in Eq. (1), such as $\boldsymbol{\beta}_{jk}$ and $\boldsymbol{\gamma}_{jk}$, without the need to include all possible observed and unobserved time-invariant factors at the county level.

One drawback of county-level fixed effects is that the influence of any time-invariant county characteristics cannot be analyzed even if information is available. In addition, if a variable does not vary much over time, the differencing in Eq. (1b) will remove a large portion of the variation in the variable. As a result, the estimated coefficient of the variable would have large standard errors and much smaller statistical significance. For example, within each county, there is little variation in commodity prices, costs of inputs, and costs of implementing irrigation technology. Thus, while these factors are considered by producers in their decisions regarding irrigation technologies and WMPs, the inclusion of county and year dummies allows for their omissions (Buller and Williams, 1990; Dridi and Khanna, 2005).

If the data only allow the construction of binary variable, y^*_{icjkt}, which is one if technology j and/or WMP k are used, then y_{icjkt} in Eq. (1) can be treated as the latent variable underlying the binary decision observed in the data. The relationship between the observed binary variable y^*_{icjkt} and the latent variable y_{icjkt} is expressed as:

$$Y^*_{icjkt} = \begin{cases} 1 & \text{if } y_{icjkt} > 0 \\ 0 & \text{if } y_{icjkt} \le 0 \end{cases} \tag{2}$$

In this case, discrete choice estimation methods such as multivariate probit or multinomial logit can be used. However, the fixed effects model could not be used since the estimating equations with binary dependent variables are nonlinear. The fixed effects cannot be differenced out in nonlinear models.

Fig. 1. Location of study sites.

3. Description of the study site, survey data and variables

This study area covers agricultural areas of Arkansas, Mississippi, and Louisiana, henceforth referred to as the Delta (Fig. 1). The Delta area is subtropical and humid, with an average annual temperature ranging from 16.3 °C to 19 °C and an annual precipitation between 967.7 mm (mm) and 1818.6 mm (NOAA NCEI, 2017). The Delta area is one of the nation's most productive agricultural areas. Arkansas ranks first nationally in total rice production (USDA NASS, 2008). Mississippi and Louisiana also rank high nationally in rice acreage. Soybean, corn and cotton accounted for 32%, 14.6% and 12.4% of total national acreage in 2007, respectively (USDA NASS, 2008). Agriculture is heavily irrigated in the region (Table 1). In 2012, Arkansas, Louisiana, and Mississippi ranked 3rd, 9th, and 17th nationally in irrigated acreage respectively, accounting for 14% of national irrigated acreage (USDA NASS, 2014). The main source of irrigation water is groundwater pumped from the shallow Mississippi River Valley Alluvial Aquifer (MRVAA) (Clark et al., 2011). Between 1994 and 2008, more than 70% of irrigated area was irrigated by groundwater. Heavy

Table 1
Crop Mix and% Irrigated by Crop.

Year of Census[a]	2007		2002		1997	
Crop	% acreage[b]	% irrigated[c]	% acreage	% irrigated	% acreage	% irrigated
Soybean	0.32	0.50	0.33	0.43	0.44	0.31
Rice	0.13	1.00	0.15	1.00	0.14	1.00
Corn	0.15	0.51	0.08	0.33	0.07	0.30
Cotton	0.12	0.58	0.17	0.50	0.17	0.41

Sources: USDA NASS. Census of Agriculture.
[a] Years of Census of Agriculture from which the sample of FRIS survey is drawn are used. For example, the sample of producers for the 2008 FRIS survey is drawn from the 2007 Census of Agriculture.
[b] The% acreage column reports the share of total acreage allocated to a crop averaged across all farms.
[c] The% irrigated column reports the share of a crop's total acreage that is irrigated.

pumping has changed the status of groundwater from historical abundance to concerns of depletion. Parts of eastern Arkansas have been designated as critical groundwater areas because groundwater levels have dropped by 15.25 m or more (Clark et al., 2011). Several major rivers in Mississippi already run dry during the summer months (Barlow and Clark, 2011). An annual gap in groundwater as large as 8.63 billion cubic meters (m^3) by 2050 is projected for Arkansas (ANRC, 2015).

Although groundwater irrigation has mitigated the impact of extreme events such as droughts, producers still suffered large income losses due to other events such as heavy rain in 2016 and flooding in 2011 and 2017. The frequencies of flooding and drought are expected to continue to increase in coming decades (Arkansas Governor's Commission on Global Warming, 2008). Furthermore groundwater supply is also impacted by variability in annual precipitation because it is partially recharged by rainwater (Czarnecki and Schrader, 2013).

Most variables used in the empirical analysis are constructed using the Farm and Ranch Irrigation Survey (FRIS) and Census of Agriculture collected by the U.S. Department of Agriculture. It is a set of repeated cross-sectional data collected in multiple years. We used 1998, 2003, and 2008 rounds. The 1988 and 1994 data were excluded because information on several key variables (such as the change in depth-to-water in wells, participation in government programs, and number of irrigation information sources) was not collected in these rounds of the FRIS survey. The FRIS sample is drawn from the population of all farms identified in the Census of Agriculture (USDA NASS, 2010). For example, the sample of producers for the 2008 FRIS survey is drawn from the 2007 Census of Agriculture. A stratified sampling process was used for each state where farms were stratified based on total irrigated areas. In each state, some farms were selected with probability one to make sure the major irrigators in each state were included. It is arguably the most comprehensive data on irrigation. It contains information on the use of irrigation technologies on a crop-specific basis. It also has information on a range of WMPs. County-level climate data, including daily temperature and precipitation data, come from the National Climatic Data Center (National Climatic Data Center, 2016). Soil quality is measured by adjusted saturated hydraulic conductivity (K_{sat})[1] using data from the Soil Survey Geographic Database (Soil Survey Staff, 2016).

Both more efficient irrigation and WMPs have been proposed as solutions to bring water use onto a more sustainable path. The critical initiatives identified in the 2014 Arkansas Water Plan Update highlight adopting conservation measures that can improve on-farm application efficiency as well as infrastructure-based solutions (such as tailwater pits and on-farm reservoir) that convert more irrigated crop area currently supplied by groundwater to surface water in eastern Arkansas (ANRC, 2015). In the Delta region, between 69% and 77% of producers utilized a gravity irrigation system (including furrow and flood irrigation) during the period 1998–2008 (USDA NASS, 2008). Producers often choose to pair gravity irrigation technologies with WMPs. Nearly 47% of producers with gravity irrigation systems used one or more WMPs in 2008 (Table 2). For instance, among producers that used gravity irrigation, 25% used laser leveling, and 14% of producers used tailwater recovery. The rates of using these WMPs fluctuated over the years. Between 1998 and 2008, an increasing share of producers used tailwater pits, but a shrinking share used alternate row irrigation or special furrow techniques. The majority of producers with gravity systems utilize more than one WMP. The sample size for each unique combination of WMPs is small, so we construct the dependent variable to include all WMPs as one single group.

Table 2
% of Farms with Gravity System that Have Used a Water Management Practice.

Year	2008	2003	1998
% of farm that used one or more WMPs	0.47	0.52	0.52
Tailwater pits	0.14	0.06	0.09
Laser leveling	0.25	0.25	–[a]
Alternate row irrigation	0.15	0.19	0.23
Water restricted from running off by diking end of field	0.14	0.18	–[a]
Reduce irrigation application rate	0.05	0.07	0.06
Shorten furrow length	0.02	0.01	0.01
Special furrowing techniques[b]	0.07	0.09	0.22
Surge flow or cablegation irrigation	0.006	0.006	0.02

Sources: USDA NASS. *Farm and Ranch Irrigation Survey*.
[a] Blank cells mean the FRIS survey did not ask about this practice.
[b] Some examples include wide-spaced bed furrowing, compacted furrowing and furrow diking.

Adapting Eq. (1) to the sample data we have at hand, Eq. (1) is modified as:

$$Y_{ic1t} = \boldsymbol{\alpha}_{c1} + \mathbf{W}_{ict}\gamma_1 + \mathbf{X}_{ict}\boldsymbol{\beta}_1 + \varepsilon_{ic1t} \tag{3}$$

$$y_{ic2t} = \boldsymbol{\alpha}_{c2} + \mathbf{W}_{ict}\gamma_2 + \mathbf{X}_{ict}\boldsymbol{\beta}_2 + \varepsilon_{ic2t} \tag{4}$$

In Eq. (3), the dependent variable y_{ic1t} is the share of producer i's farm land irrigated with sprinklers in period t. In Eq. (4), the dependent variable y_{ic2t} is the share of producer i's farm land under gravity irrigation combined with WMPs in period t. The definitions and the summary statistics of variables are reported in Table 3.

For all climate variables, five versions are constructed to assess which time frame is most likely used by producers when making irrigation decision in response to changes in climatic conditions: the previous year, previous 5 years, previous 10 years, previous 20 years, and previous 30 years. For example, for variables that come from the 2008 FRIS survey, these periods are 2007 (previous year), 2002–2007 (previous 5 years), 1998–2007 (previous 10 years), 1988–2007 (previous 20 years), 1978–2007 (previous 30 years). Only climate data during the growing season which is between April and October in the Delta region, are used.

No clearly increasing or decreasing trends are observed for either MDT or total precipitation (Figs. 2 and 3). For all the FRIS survey years, the CVs of MDT years are all above 0.1 (Table 4). This is consistent with the variations over the years observed in Fig. 2. The standard deviations of CVs, which give a sense of the variations in CVs across counties, range between 0.118 and 0.137. The small standard deviations are expected since the study area only covers a relatively small region; therefore, spatial variations in climate factors are limited. However, the magnitudes of the standard deviations are about 17–25% of the magnitudes of CVs, so they are not near zero. The CVs of total precipitation are slightly higher than that of daily temperature. The standard deviations range from about 18–40% of the magnitudes of CVs. For all five measures that use different length of previous period, the share of months with severe droughts has increased over the years. The share of days with intensive precipitation has stayed around 20%, with no clearly increasing or decreasing trend over the years.

As shown in Table 5, the measures of the same climate variable exhibit strong correlations. This is due partly to overlaps between different measures. For example, the previous 30 years includes previous 20 years and previous 10 years. The magnitudes of correlations are much larger among temperature measures than among precipitation measures. The measures from previous years have lower correlations with measures from other periods.

[1] Values are adjusted to approximate 10% of estimated K_{sat}, which is based on the soil surface texture of the soil mapping unit in each county (Saxton et al., 1986). The adjusted K_{sat} values are assumed to reasonably represent the ability of unsaturated soil to transmit water over the course of one year.

Table 3
Variable Definitions and Summary Statistics.

Variable Name	Year	2008 (N = 1,528)		2003 (N = 1,520)		1998 (N = 1,506)	
	Description	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
% Sprinkler	Percent of crop area irrigated by sprinklers	0.16	(0.31)	0.22	(0.32)	0.18	(0.33)
% Gravity	Percent of crop area irrigated by gravity	0.77	(0.32)	0.69	(0.33)	0.78	(0.33)
% WMP	Percent of crop area irrigated by gravity combined with WMP	0.3	(0.44)	0.29	(0.44)	0.39	(0.47)
Experience	Years of experience on-farm	23.22	(13.75)	19.89	(12.83)	22.13	(13.62)
Farm size	Farm size in 1,000 ha	0.56	(0.90)	0.43	(0.82)	0.49	(0.89)
% Rented in	Percent of land that is rented in	0.57	(0.35)	0.53	(0.35)	0.68	(0.35)
Crop diversity	Number of crop categories produced on a farm (grain crops, cash crops, fruits and vegetables, fodder crops)	1.65	(0.67)	1.53	(0.70)	1.64	(0.71)
% Rice	Percent of crop area in rice	0.28	(0.37)	0.33	(0.40)	0.4	(0.40)
Water cost	Energy cost of water in $/m^3, 2008 dollars	0.03	(0.07)	0.04	(0.05)	0.03	(0.04)
% Groundwater	Percent of crop area irrigated by ground water	0.77	(0.30)	0.72	(0.32)	0.85	(0.28)
Depth increased	Depth-to-water in wells increased in the last five years	0.11	(0.29)	0.08	(0.29)	0.14	(0.37)
Program participation	Percent of farms in the county participated in government programs, Lagged	0.15	(0.14)	0.24	(0.13)	0.25	(0.10)
N info source	Number of irrigation information sources	1.85	(1.62)	1.95	(1.27)	1.45	(1.31)

Sources: USDA NASS. *Census of Agriculture*; *Farm and Ranch Irrigation Survey*.

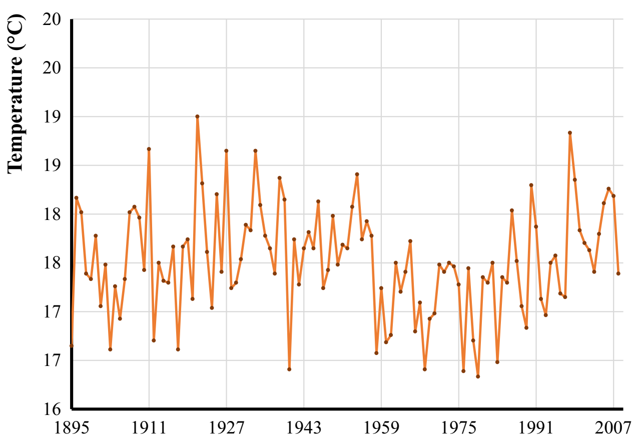

Fig. 2. Average annual temperature in Arkansas, Louisiana and Mississippi, 1895–2007. *Source*: NOAA NCEI.

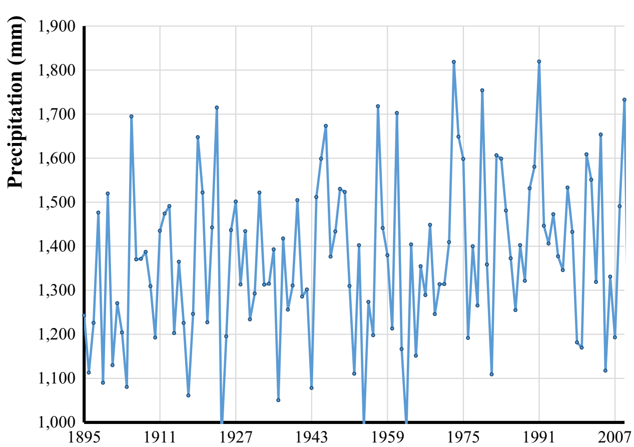

Fig. 3. Average annual total precipitation in Arkansas, Louisiana and Mississippi, 1895–2007. *Source*: NOAA NCEI.

Following the literature, three groups of variables are included in $\mathbf{X}_{ic}$. The first group of variables measures producer and farm characteristics. Years of on-farm experience is used to measure producer characteristic. Total years of on-farm experience ranged from 19.89 years in 2003 to 23.22 years in 2008 (Table 3). Farm characteristics include farm size, tenure status, and crop mix. The size of farm averaged between 425.25 and 558.9 ha (ha) during the sample period. Although field slope has been identified in the literature as an important factor, it is not included because the study site is in the Mississippi River Delta region with flat floodplain landform. Because land tenure may impact investment in new irrigation technology and/or WMPs, we construct a variable to measure the percent of land that is rented from others. In 2003, only 53% of land was rented, less than in 1998 (68%) and 2008 (57%). Crop diversity is a categorical variable that ranges from 1 to 4 and is a count of crop categories (grain crops, cash crops, fodder crops, and fruits and vegetables). The share of total farm land in rice is also included to reflect the crop mix. In 2008, 28% of all acreage was planted in rice, down from 40% in 1998.

The second group measures characteristics of water resources with three variables. The cost of water is calculated as the farm level energy cost per m^3 of groundwater pumped. The extent of reliance on groundwater is measured by the percent of farm acreage irrigated by groundwater. Agriculture in the Delta region relies heavily on groundwater for irrigation. The share of groundwater use remained above 70% over the years of this study (Table 3). A dummy variable is included that equals one if the depth-to-water in wells on-farm had increased over the previous five years. Somewhat surprisingly, during the sample period, only around 10% of the producers have reported an increase in depth-to-water. This is in sharp contrast to the declining groundwater levels and forthcoming groundwater gaps reported by state and local governments (e.g., ANRC, 2015). Part of the explanation is that groundwater levels are falling rapidly only in parts of the region (e.g., Lonoke County in Arkansas) but not in others. It could also be that when first drilled, producers' wells were deeper than the minimum depth-to-groundwater, and because of this, producers are unable to accurately describe how their groundwater is changing until their ability to irrigate is impeded.

Variables in the third group measure program participation and sources of irrigation information. Since the use of irrigation technologies and/or WMPs (the dependent variables) would affect the decision to participate in programs that offer financial and/or technical assistance during the same year, the lagged variable is used so that it measures the share of producers in the county that participated in any government programs in the previous period. Such share had remained as low as 25% in 1998 and 2003 and dropped to 15% in 1998 (Table 3). The FRIS survey also asked the producers to list all information sources they had relied on for guidance in reducing irrigation costs or conserving irrigation water. The sources include extension agents or university specialists, private irrigation

Table 4
Summary Statistics of Climate Variables.

Previous Years[a]	Year	Daily Temperature (°C)		% of months with severe droughts	Total Precipitation (mm)		% of days with intensive precipitation
		Mean	Coefficient of Variation		Mean	Coefficient of Variation	
1	2008	23.612		0.066	640.817		0.201
		(18.952)		(0.154)	(131.978)		(0.069)
	2003	24.716		0.024	678.383		0.194
		(18.780)		(0.059)	(206.477)		(0.072)
	1998	23.576		0.000	755.675		0.228
		(18.883)		0.000	(149.758)		(0.069)
5	2008	23.942	0.121	0.174	675.386	0.232	0.212
		(18.978)	(0.022)	(0.067)	(114.884)	(0.075)	(0.046)
	2003	23.836	0.137	0.166	616.915	0.210	0.201
		(19.042)	(0.029)	(0.116)	(120.447)	(0.083)	(0.047)
	1998	23.968	0.118	0.012	713.232	0.153	0.220
		(18.915)	(0.021)	(0.028)	(105.664)	(0.056)	(0.050)
10	2008	23.889	0.130	0.170	646.151	0.227	0.207
		(18.993)	(0.025)	(0.063)	(112.979)	(0.061)	(0.041)
	2003	23.902	0.128	0.089	665.074	0.202	0.211
		(18.957)	(0.025)	(0.053)	(107.772)	(0.048)	(0.043)
	1998	24.015	0.117	0.017	730.148	0.235	0.218
		(18.943)	(0.021)	(0.025)	(106.020)	(0.066)	(0.043)
20	2008	23.952	0.124	0.094	688.162	0.242	0.212
		(18.954)	(0.023)	(0.028)	(106.451)	(0.048)	(0.037)
	2003	23.963	0.123	0.052	683.539	0.247	0.208
		(18.940)	(0.023)	(0.021)	(102.972)	(0.064)	(0.037)
	1998	23.993	0.120	0.025	708.330	0.245	0.213
		(18.974)	(0.022)	(0.022)	(97.409)	(0.059)	(0.035)
30	2008	23.958	0.124	0.074	687.603	0.246	0.211
		(18.968)	(0.023)	(0.020)	(99.492)	(0.049)	(0.033)
	2003	23.961	0.121	0.049	701.853	0.253	0.202
		(18.938)	(0.022)	(0.017)	(96.520)	(0.044)	(0.033)
	1998	24.036	0.115	0.032	708.101	0.246	0.194
		(18.855)	(0.020)	(0.027)	(87.986)	(0.044)	(0.035)

Note: Standard deviations reported in parentheses.
[a] Number of years from previous periods used to construct the climate variables.

specialists or crop consultant, irrigating equipment dealers, local irrigation district, government specialists from the NRCS, local conservation district or other federal or state agencies, media, neighbors, internet, etc. The number of irrigation information sources is used and can range from 0 to 9. The numbers observed in the data averaged less than 2 in all years, indicating somewhat limited access to irrigation information. Two year dummies are included, one for the year 1998 and one for the year 2003.

Since the FRIS data are repeated cross-sections in nature, county-level fixed effects can be used to control for any unobserved time-invariant county characteristics in estimating Eqs. (3) and (4). To increase the efficiency of estimation, the equations for the percent irrigated by sprinklers (Eq. (3)) and that for the percent irrigated by gravity in conjunction with WMPs (Eq. (4)) are estimated jointly using seemingly unrelated regressions (SUR), since they measure the use of irrigation practices of the same farm. The equation for the percent irrigated by gravity without WMPs is not included since the three percent variables would add up to be 100% for most farms.

4. Empirical results

The estimation results of the county fixed effects model are reported in Table 6.[2] Estimation results of Eq. (3) are reported in columns 1a-1e. Each column is a specification that uses different lengths of previous period to construct climate variables. Estimation results of the five specifications of Eq. (4) are reported in columns 2a-2e. For both Eqs. (3) and (4), the impacts of MDT are similar across specifications. For example, in the model for percent of crop area irrigated by sprinklers, the coefficients of MDT are negative in all specifications (columns 1a-1e) and statistically significant except for the specification using the previous 10 years. The estimated coefficients of MDT are all positive in the model for percent irrigated by gravity combined with WMPs (columns 2a-2e). The highly consistent results are likely due to the strong correlations among different measures of MDT observed in Table 5.

The signs of the coefficients make sense and are consistent with findings of previous studies (Olen et al., 2015). It is likely that during sustained periods of above average temperatures, the increased rates of evaporation would largely offset the benefits of using sprinkler irrigation. Therefore, producers are more likely to opt for gravity irrigation and achieve water savings through the use of better Water Management Practices rather than sprinkler irrigation. Interestingly, the magnitude of the coefficient of MDT for sprinklers is greatest using the 30-year measure. In contrast, the coefficients of MDT for gravity with WMPs are larger using the previous year or 20-year measures. Sprinklers are generally a more capital intensive form of irrigation technology. Producers' planning time horizons tend to be longer for capital intensive technologies. If producers find sprinkler irrigation less suitable to periods of above-average temperatures, and temperatures have been high for a long time, then producers will move away from more-expensive technology towards practices that better meet their irrigation needs. Because gravity irrigation and most WMPs are less capital intensive, producers may be more easily able to make

[2] As a robustness check, in another specification, fixed effects are used at the state level instead of at the county level. The results on most variables are largely consistent in terms of the signs, levels of statistical significance, and magnitudes of the estimated coefficients.

Table 5
Correlations among Climate Variables.

Mean Daily Temperature				
	Previous year	Previous 5 years	Previous 10 years	Previous 20 years
Previous 5 years	0.950***			
Previous 10 years	0.930***	0.985***		
Previous 20 years	0.918***	0.974***	0.989***	
Previous 30 years	0.903***	0.962***	0.981***	0.997***
Daily Temperature, Coefficient of Variation				
	Previous 5 years	Previous 10 years	Previous 20 years	
Previous 10 years	0.968***			
Previous 20 years	0.965***	0.989***		
Previous 30 years	0.961***	0.981***	0.996***	
% of months with severe droughts				
	Previous year	Previous 5 years	Previous 10 years	Previous 20 years
Previous 5 years	−0.152*			
Previous 10 years	−0.479***	0.403***		
Previous 20 years	−0.257***	0.636***	0.921***	
Previous 30 years	−0.230***	0.870***	0.735***	0.904***
Total Precipitation				
	Previous year	Previous 5 years	Previous 10 years	Previous 20 years
Previous 5 years	0.542***			
Previous 10 years	0.525***	0.958***		
Previous 20 years	0.565***	0.923***	0.974***	
Previous 30 years	0.592***	0.901***	0.947***	0.984***
Total Precipitation, Coefficient of Variation				
	Previous 5 years	Previous 10 years	Previous 20 years	
Previous 10 years	0.795***			
Previous 20 years	0.455***	0.601***		
Previous 30 years	0.397***	0.514***	0.742***	
% of days with intensive precipitation				
	Previous year	Previous 5 years	Previous 10 years	Previous 20 years
Previous 5 years	0.623***			
Previous 10 years	0.531***	0.875***		
Previous 20 years	0.465***	0.733***	0.866***	
Previous 30 years	0.448***	0.684***	0.806***	0.954***

*Denotes correlation is statistically significant at 10%, **at 5% and ***at 1%.

changes to their irrigation system and, as such, are less likely to have their decision to opt for this irrigation technology impacted by average temperatures during the previous 20 and 30 years.[3]

While mean daily temperatures appear important to producers' irrigation decisions, variations in temperature do not. The coefficient of variation (CV) variables all have negative coefficients in the model for sprinkler irrigation and none is statistically significant. In the model for WMPs, only the CV of mean daily temperature of the previous 20 years seems to have a negative and statistically significant impact. Burke and Emerick (2006) have offered a possible explanation for the negative impact: when there is a larger variation in climate, producers are less likely to recognize changes in climate and, thus, are less likely to adapt to those changes. Evidence also shows that CV constructed using a shorter length of time may not provide a good measure of variations in climate. In the model for WMPs, the signs of CV switched from positive in specifications using shorter previous periods to negative in specifications using longer previous periods.

Drought occurrence does appear to impact producers' irrigation decision-making. A larger percent of months with severe drought during the previous year predicts a larger share of area irrigated by sprinkler. This is consistent with the argument of Zilberman et al. (1995) that extreme events, such as droughts, are likely to push producers over the investment hurdle and boost the rates of adopting conservation practices. For example, during the 1987–1991 California droughts, a large share of cotton producers (one of the major field crops in California) replaced furrow irrigation with sprinkler irrigation (Zilberman et al., 1995). A higher drought occurrence observed during the longer time horizon, however, has the opposite effect. The sign of the coefficient using the previous 30 years measure changes to negative and is statistically significant at the 5% level. In contrast, in the model for percent of area irrigated by gravity with WMPs, the coefficient of severe droughts is positive and statistically significant in the specifications using previous 5 years and previous 30 years. One possible explanation is that farmers may associate higher drought occurrences with a hotter environment and permanent decline in water availability. As a result, sprinkler irrigation would be less favored due to evaporation losses. WMPs, such as tailwater pits, would be favored because these types of technologies can augment water supply by reusing irrigation run off and capturing rainwater.

The impact of total precipitation is similar across all five specifications. The coefficients for total precipitation are negative in all specifications for both models. The coefficients are also statistically significant for measures using the previous 1-, 5-, and 20-year time periods for percent of area irrigated by sprinklers as well as for measures using the previous 1- and 20-year periods for gravity

[3] In an alternative specification, the squared mean daily temperature is also included. The estimated coefficient on the squared term is statistically significant but the magnitudes are small, in the order of 10^{-6}. The estimated results on other variables are largely the same.

Table 6
Factors that Influence the Choice of Irrigation System and Water Management Practices (WMPs) with County Fixed Effects.

Dependent variables:	% of crop area irrigated by sprinklers					% of crop area irrigated by gravity combined with WMPs				
	(1a)	(1b)	(1c)	(1d)	(1e)	(2a)	(2b)	(2c)	(2d)	(2e)
Climate variables measured using	Previous year	Previous 5 years	Previous 10 years	Previous 20 years	Previous 30 years	Previous year	Previous 5 years	Previous 10 years	Previous 20 years	Previous 30 years
Mean daily temperature	−0.035*	−0.042***	−0.036	−0.041*	−0.059***	0.061***	0.038*	0.076***	0.025	0.014
	(0.018)	(0.016)	(0.023)	(0.023)	(0.022)	(0.019)	(0.020)	(0.025)	(0.024)	(0.029)
CV of daily temperature	−0.284	−1.425	−0.254	−1.548	−0.906	0.748	0.289	2.188	−3.835*	−2.694
	(0.640)	(0.975)	(1.395)	(1.514)	(1.593)	(0.765)	(1.281)	(1.610)	(1.965)	(2.146)
% months with severe droughts	0.112*	−0.099	0.147	0.080	−0.889**	−0.077	0.319***	−0.269	−0.202	1.086**
	(0.067)	(0.080)	(0.139)	(0.294)	(0.373)	(0.082)	(0.116)	(0.167)	(0.380)	(0.467)
Total precipitation	−0.000170***	−0.000333***	−0.000252	−0.000383**	−0.000254	−0.000170**	−0.000168	−0.000200	−0.000662***	−0.000373
	(0.000064)	(0.000123)	(0.000165)	(0.000193)	(0.000252)	(0.000077)	(0.000148)	(0.000190)	(0.000237)	(0.000291)
CV of total precipitation		0.081	0.048	−0.010	0.085		−0.021	0.151	−0.172	−0.087
		(0.097)	(0.126)	(0.167)	(0.249)		(0.121)	(0.154)	(0.249)	(0.309)
% days with intensive precipitation	0.262**	0.741***	1.032***	1.286***	1.380***	0.274*	−0.015	−0.711**	−0.704**	0.097
	(0.121)	(0.174)	(0.245)	(0.296)	(0.289)	(0.156)	(0.213)	(0.286)	(0.356)	(0.353)
Experience	−0.00179***	−0.00180***	−0.00180***	−0.00177***	−0.00178***	0.00149	0.00155*	0.00157*	0.00156*	0.00156*
	(0.000594)	(0.000596)	(0.000595)	(0.000596)	(0.000598)	(0.000941)	(0.000940)	(0.000940)	(0.000942)	(0.000943)
Farm size	1.607**	2.044***	1.514	1.923*	2.546**	−2.585***	−1.558	−3.222***	0.070	−0.082
	(0.815)	(0.778)	(1.126)	(1.096)	(1.032)	(0.881)	(0.963)	(1.185)	(1.222)	(1.415)
% Rented in	−0.0559**	−0.0567**	−0.0573**	−0.0559**	−0.0554**	0.0886**	0.0884**	0.0937**	0.0901**	0.0892**
	(0.0251)	(0.0252)	(0.0250)	(0.0251)	(0.0251)	(0.0376)	(0.0376)	(0.0377)	(0.0376)	(0.0375)
Crop diversity	−0.0528***	−0.0547***	−0.0555***	−0.0568***	−0.0559***	0.0721***	0.0728***	0.0718***	0.0741***	0.0726***
	(0.0168)	(0.0164)	(0.0165)	(0.0166)	(0.0167)	(0.0221)	(0.0218)	(0.0220)	(0.0221)	(0.0221)
% Rice	−0.438***	−0.440***	−0.437***	−0.433***	−0.436***	0.0944**	0.0960**	0.0931**	0.0876*	0.0909**
	(0.0367)	(0.0370)	(0.0368)	(0.0370)	(0.0369)	(0.0453)	(0.0457)	(0.0457)	(0.0464)	(0.0462)
Soil permeability	0.000256	0.000144	0.000375	0.000270	−0.000159	−0.00121	−0.000966	−0.000927	−0.00133	−0.000960
	(0.000691)	(0.000723)	(0.000746)	(0.000755)	(0.000679)	(0.000819)	(0.000826)	(0.000948)	(0.000858)	(0.000825)
Water cost, log	−0.00591	−0.00479	−0.00525	−0.00444	−0.00387	0.0128	0.0119	0.0121	0.0121	0.0108
	(0.00774)	(0.00775)	(0.00774)	(0.00769)	(0.00766)	(0.0101)	(0.0101)	(0.0101)	(0.0100)	(0.0100)
% Groundwater	−0.00145	−0.00952	−0.00640	−0.00952	−0.0154	−0.0363	−0.0282	−0.0330	−0.0294	−0.0196
	(0.0371)	(0.0371)	(0.0370)	(0.0369)	(0.0370)	(0.0511)	(0.0511)	(0.0511)	(0.0509)	(0.0511)
Depth increased	−0.0249	−0.0269	−0.0266	−0.0257	−0.0256	0.0290	0.0312	0.0309	0.0308	0.0297
	(0.0167)	(0.0166)	(0.0165)	(0.0165)	(0.0167)	(0.0351)	(0.0352)	(0.0352)	(0.0350)	(0.0352)
Program participation	−0.233**	−0.235**	−0.243***	−0.236**	−0.220**	0.215**	0.215**	0.218**	0.194*	0.198*
	(0.0936)	(0.0927)	(0.0933)	(0.0920)	(0.0907)	(0.105)	(0.105)	(0.106)	(0.104)	(0.103)
N info source	0.00488	0.00453	0.00528	0.00489	0.00409	0.0557***	0.0560***	0.0554***	0.0554***	0.0559***
	(0.00893)	(0.00897)	(0.00897)	(0.00902)	(0.00910)	(0.00991)	(0.00994)	(0.00995)	(0.00994)	(0.0100)
Year 1998	0.112***	0.110***	0.118***	0.110***	0.108***	0.0654*	0.0820**	0.0668*	0.0597	0.0700*
	(0.0292)	(0.0301)	(0.0305)	(0.0289)	(0.0288)	(0.0364)	(0.0377)	(0.0391)	(0.0368)	(0.0368)
Year 2003	0.0911***	0.0813**	0.0789***	0.0761***	0.0695***	−0.0534	−0.0320	−0.0406	−0.0359	−0.0180
	(0.0331)	(0.0318)	(0.0285)	(0.0277)	(0.0266)	(0.0405)	(0.0375)	(0.0344)	(0.0334)	(0.0326)
Constant	0.747***	0.722**	0.634*	0.749**	0.729**	0.271	0.217	0.143	0.254	0.218
	(0.272)	(0.310)	(0.381)	(0.292)	(0.296)	(0.272)	(0.309)	(0.382)	(0.292)	(0.295)
N	4,521	4,521	4,521	4,521	4,521	4,521	4,521	4,521	4,521	4,521
Adjusted R^2	0.445	0.446	0.447	0.447	0.447	0.445	0.446	0.447	0.447	0.447

Note: Standard errors reported in parentheses; *significant at 10%; **significant at 5%, ***significant at 1%.
a. Each pair of columns with the same letter (e.g., Columns 1a and 2a) are estimated jointly using seemingly unrelated regressions (SUR).
b. These variables are interacted with farm size: all temperature and precipitation measures; Soil permeability (K_{sat}).

with WMPs. This result is as expected. When higher annual rainfall reduces the need for irrigation, producers are simply less likely to switch to sprinklers or use any WMPs. No consistent impact of the CV of total precipitation is observed. Its coefficient is not statistically significant for any specification. The signs also changed between specifications. Again, this may indicate that CV or variance is not a good measure of the variations in weather that is relevant to producers' decision making.

Among the set of climate variables examined, the occurrence of intensive precipitation seems to have the strongest impact on producers' decisions regarding irrigation practices. As the percent of days with intensive precipitation increases, the percent of area irrigated by sprinklers also increases. While the coefficient for intensive rainfall is for gravity irrigation with WMPs is positive and statistically significant at 10% for the previous year, it is negative and statistically significant at 5% for the previous 10 and 20 years. Putting these two sets of results together, one possible explanation is that when intensive rainfall is an immediate but unusual occurrence, producers are more likely to use WMPs, such as tailwater pits, to collect excessive rainfall. However, when periods of intensive rainfall are common and have been occurring over a long period, the utilization of sprinklers, which puts less water onto a field than gravity irrigation, may be preferred to minimize water use and prevent crop loss that could occur if a round of flood irrigation was immediately followed by intensive flood irrigation.

4.1. Results on other control variables

The estimation results on all other control variables except for farm size are highly consistent across specifications with different climate variables. The estimated coefficients of most variables have the same signs, similar magnitudes, and levels of statistical significance. This indicates the robustness of the results to alternative specification of climate variables. The estimated coefficients of farm size are different in some of the specifications, probably because climate variables are interacted with farm size in the regressions.

Farm experience has opposite impacts on the use of sprinklers and the use of WMPs. The estimated coefficients on years of experience are negative and statistically significant for sprinkler irrigation but are positive and statistically significant for gravity irrigation with WMPs. Koundouri et al. (2006) also found a negative effect of age on the likelihood of using more-efficient irrigation technology. Switching from gravity to sprinklers requires knowledge of new irrigation techniques. Other factors, such as education, may be more important in acquiring new knowledge than on-farm experience. In contrast, most WMPs, such as laser leveling and tailwater pits, require more knowledge of the farm, which increases with years of on-farm experience, thus, facilitating the adoption of WMPs. So, more experienced producers may prefer WMPs over sprinkler irrigation.

Farm size also shows different influences on the use of sprinklers and the use of WMPs. The estimated coefficients of farm size are positive and statistically significant for sprinkler irrigation, while negative and statistically significant for gravity irrigation with WMPs. Larger farms tend to be more likely to adopt capital intensive sprinkler irrigation because they enjoy economies of scale and have better access to credit for on-farm investment. This positive relationship between farm size and sprinkler adoption has also been exhibited in previous studies (e.g. Schuck et al., 2005; Huang et al., 2017). Additionally, sprinklers may be viewed as a more-practical irrigation decision on large farms, because it reduces the amount of labor needed relative to forms of gravity irrigation.

Tenure status also seems to influence irrigation practice decisions. The coefficients of the percent of land rented are negative and statistically significant for sprinkler irrigation. The large initial capital investment associated with sprinkler irrigation may discourage producers operating largely on rented land. This is consistent with findings from some previous studies that landowners are more likely to use conservation practices than producers that rent (Lynne et al., 1988). In some cases, the rental arrangement may not allow big changes in irrigation systems (Hill et al., 2003). A surprising finding is that a higher share of rented land also predicts increased use of WMPs. The estimated coefficients of the percent of land rented are positive and statistically significant for gravity irrigation with WMPs. For some WMPs such as tailwater pits, it may be that it is easier to rent out land with tailwater pits. Irrigation availability is one of the factors that impact the amount of land rented/leased (Hill et al., 2003). Crop share is the most common rental arrangement for all farm types and crops in the Delta region, where rent is paid as a share of the crop (Hill et al., 2003). Therefore, both landowners and operators are likely to be involved in making capital investments including irrigation investments. This may also explain the positive relationship between share of rented land and the use of WMPs.

The impact of crop diversity on sprinkler adoption is negative and statistically significant for sprinkler irrigation but positive and statistically significant for gravity irrigation with WMPs. This likely occurs because producers find it more suitable to institute a single gravity irrigation technology while implementing multiple WMPs to better meet the irrigation needs of each different crop produced. For example, because different crops are grown in different times of the year, farms demand irrigation water for longer periods during the year. WMPs, such as tailwater pits, can meet this demand by increasing water stored on-farm. As expected, producers who grow rice are less likely to implement sprinkler irrigation, instead opting for gravity irrigation with WMPs. Because rice production requires large quantities of irrigation water, the most common form of rice irrigation is flooding (a form of gravity irrigation). As such, it is expected that producers would attempt to make the rice irrigation more efficient through the implementation of WMPs rather than by way of sprinkler irrigation, which would be unlikely to provide sufficient water to maintain yields. Previous studies have shown that higher soil permeability (K_{sat}) is associated with a greater likelihood of sprinkler irrigation and a lower likelihood of gravity irrigation with WMPs (Negri and Brooks, 1990; Mendelsohn and Dinar, 2003). While the estimated coefficients of this study are consistent with these findings, the coefficients here are not statistically significant in any time period. This may be because soil variable is only available at the county level. With the use of the county fixed effects, a large portion of the variation arising from soil differences is removed, and, thus, the estimated coefficients would have large standard errors and lose statistical significance.

Somewhat surprisingly, all three variables that measure the characteristics of water resources do not seem to influence the use of irrigation practices. The estimated coefficients of the cost of water, which are negative for sprinkler irrigation and positive for gravity irrigation with WMPs, are not statistically significant. While this result is consistent with the findings of Huang et al. (2017), it diverges from the positive relationship between the cost of water and the use of sprinkler irrigation identified in several previous studies (e.g., Caswell and Zilberman, 1986; Negri and Brooks, 1990). The effect of water cost may have been largely absorbed by choice of crops. Moreno and Sunding (2005) also found that the choice of sprinkler technology is relatively unresponsive to water price after accounting for the influence of water price on land allocation decisions. The coefficients of the percent reliance on groundwater are negative for the percent of area irrigated with sprinklers and for gravity irrigation with WMPs. None of the coefficients are statistically significant. Likewise, while the coefficients of the dummy variable that equals one if depth-to-groundwater had increased were expected to be positive for sprinkler irrigation, they are negative but do not exhibit statistical significance for either dependent variable. One additional explanation is that all three variables are likely to be highly correlated with the characteristics of the aquifers in the area; therefore, there may not be many variations within the county. If this supposition is correct, then the use of county-level fixed effects model may have reduced the level of statistical significance by differencing out a large of variations in these variables. However, in the alternative specifications that replace county-level fixed effects with state level fixed effects, only depth-to-water has become statistically significant at 10%.

For both models and in all five specifications, the coefficients for participation in government programs are statistically significant and negative for sprinklers and statistically significant and positive for gravity with WMPs. If only the results for sprinklers were considered, this finding would not be consistent with previous studies which have shown that participation in government programs is a strong predictor of conservation technology adoption (e.g. Amosson et al., 2009). However, because these coefficients are positive for the use of gravity and WMPs, we can reasonably conclude that producers who participate in government programs in the study region are more likely to adopt WMPs in lieu of more-efficient irrigation technologies. Such a conclusion is reasonable given that many local governments in the region have been promoting WMPs, such as tailwater recovery pits, as a way to increase surface water use (e.g., ANRC, 2015). For example, Arkansas offers a tax credit which allows producers to claim up to $9000 for conversion to surface water or land leveling. In Mississippi, federal programs, such as the Mississippi River Basin Healthy Watersheds Initiative, Environmental Quality Incentives Program, and the Regional Conservation Partnership Program, provide technical and financial assistance to producers in the MRVAA and have contributed to the voluntary implementation of water recycling and conservation practices, such as tailwater recovery ditches and on-farm storage reservoirs (Barlow and Clark, 2011). The policy nudge toward surface water use may also reduce the popularity of sprinklers since modern irrigation technologies are more likely to be used on fields with groundwater supplies because groundwater is usually delivered at higher pressure (Caswell and Zilberman, 1986). The number of irrigation information sources is statistically significant at the 1% level and positive for gravity irrigation with WMPs in all five specifications. The same coefficients are positive but not statistically significant for sprinkler irrigation. The finding on WMPs is largely consistent with previous studies that have shown that more sources of information lead to an increase in the adoption of modern irrigation technology (e.g. Genius et al., 2013). The result on sprinkler irrigation lends further support to the influence of the specific direction of local government programs in favor of WMPs.

5. Conclusions

This paper examines whether climatic factors play a role in producers' irrigation decisions. We find that even in highly irrigated agriculture such as the one in the study area, producers consider climatic conditions when making their irrigation decisions. Therefore, improving the availability of climate information to producers can help them maintain productivity and profitability in the environment of a shrinking and more volatile irrigation water supply. Climate information would be more valuable in developing countries where most producers do not have means such as crop insurance to protect them from losses due to climate risks.

Not all aspects of climate are factored into producers' irrigation decisions. Both the average climate conditions and the occurrences of extreme weather events have predictive powers of producers' irrigation decisions. The coefficients of variation of temperature and precipitation do not seem to matter. One possible explanation is that measures such as average temperature and the occurrence of intensive rainfall are more visible to and easily interpreted by producers. As such, these aspects are more likely to be considered by producers. This has important implications for climate research that examines either the impacts of climate change or how various groups of individuals adapt to climate change. Many existing studies have only included the mean and variance of temperature and precipitation in their empirical specifications. Our research points to the importance of including the occurrence of extreme weather events as a factor. Extension efforts should also be put in translating climate information into formats easily understood by producers.

The results show that long-term climate patterns weigh more in producers' decisions regarding the use of sprinklers. Both long-term and short-term climate patterns seem to affect producers' decisions regarding the use of WMPs. We also find producers may respond differently to the same change in long-term and short-term climate patterns. For example, a higher occurrence of drought in the previous year is associated with a higher rate of sprinkler irrigation while an increasing trend of drought occurrence during the previous 30 years predicts the opposite. Our findings suggest that future studies on the relationship between climate and agricultural activities should not settle on a specific length of time period. Research findings would be more robust if different lengths of previous periods were used to construct the climate variables.

It should also be noted that some of our findings may be specific to the study area. For example, the occurrence of intensive precipitation has a much larger impact than the occurrence of droughts. This is probably because the study area is highly irrigated and thus flooding may cause more crop damage than droughts. The impacts of the average climate conditions (mean daily temperature and annual total precipitation) are largely the same across specifications with measures using different previous periods. This finding is also likely to be specific to the study area where average temperature and precipitation did not exhibit significant increasing or decreasing trends during the last century.

Acknowledgements

This project was supported by grants from the Arkansas Rice Research and Promotion the Board and Arkansas Soybean Promotion Board, and Arkansas Water Resource Center and the U.S. Geologic Survey of the 104B research grant program. We thank Becky Cross, the former Regional Director, and Jill Bishop, Deputy Regional Director of USDA's National Agricultural Statistics Service (NASS) Delta Regional Field Office for providing access to the data used in this research.

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