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Key Points:
- About 77% of Arkansas producers use two or more groups of WMPs to manage multiple aspects of irrigation
- For all WMP groups, a producer's WMP use positively correlates with WMP use by family members, friends, or neighbor producers
- Using water flow meters positively correlates with total irrigated acres, irrigated acres in rice, and irrigated acres in soybean

Supporting Information:
- Supporting Information S1

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Water Management Practices: Use Patterns, Related Factors, and Correlations With Irrigated Acres

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Abstract This study describes the water management practice (WMP) use patterns by producers in Arkansas, USA, identifies the factors related to producers' choices among WMP groups, and examines the correlations between WMP uses and irrigated acreage. Using data from the 2016 Arkansas Irrigation Survey, WMPs are divided into four groups: field management, water flow control, water recovery/storage, and advanced irrigation scheduling practices. We find that about 77% of producers in the study area use two or more groups of WMPs to manage multiple aspects of irrigation, but that the factors that are associated with choices of WMPs vary by WMP group. Regression results show that the use of water flow meters, providing producers with education on the looming groundwater shortage problems and awareness of financial assistance available for conservation efforts, such as the state tax credits program, and use of WMPs by family members, friends, and neighbors are associated with increased use of WMPs. However, we find that producers that are older, have smaller farms, and rely more on groundwater are less likely to use some of the WMPs. Regression results also show that using water flow meters positively correlates with total irrigated acres, irrigated acres in rice, and irrigated acres in soybeans, and that for soybeans using more groups of WMPs is associated with a reduced extent of irrigated acreage. This study contributes to the small economics literature on WMPs and provides a more comprehensive picture of how producers use different WMPs to manage irrigation.

1. Introduction

Water shortage is among the biggest challenges in agriculture production. It is estimated that, partly due to the lack of freshwater, cereal grains per capita could decline by 14% between 2008 and 2030, which would result in nearly one billion people worldwide suffering from malnutrition (FAO, 2017; Funk & Brown, 2009). Using more efficient irrigation technologies is a commonly proposed solution to reduce water use. For example, sprinkler irrigation reduces the amount of irrigation water applied relative to gravity irrigation by reducing percolation below the root zone and eliminating field runoff. However, the focus on more efficient irrigation technologies may miss important aspects of water management. Switching to a more efficient irrigation technology may not always be the best option for a producer. For example, the large initial capital investment often required by more efficient irrigation technologies may make them unaffordable. Instead, a wide range of water management practices (WMPs) could be used to improve the performance of existing irrigation systems (Schaible & Aillery, 2012). For example, pipe hole selection computer software can better match the rate of water flow with the size and the length of a furrow (Henry et al., 2018). On-farm reservoirs can store irrigation and storm water runoff for future use (Henry et al., 2018). Precision grading can minimize runoff and increase irrigation uniformity (Sullivan & Delp, 2012). Evapotranspiration-based or soil moisture-based irrigation scheduling practices can time irrigation better to meet crop water demand as dictated by field and weather conditions.

Although there is a relatively large literature on the adoption of best management practices in the agricultural sector (e.g., Baumgart-Getz et al., 2012; Prokopy et al., 2008), the economics literature is small and most studies focus on land and soil management practices used by producers outside the United States (e.g., Manda et al., 2016; Marenya & Barrett, 2007; Teklewold et al., 2013). The economic literature on WMPs is even smaller, partly due to the lack of data. Producers can choose from many different WMPs. Suitable WMPs also vary by locations. Therefore, a study on producers' use of WMPs is local in nature and

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requires detailed information on WMPs. Huang, Xu, et al. (2017) and Knapp and Huang (2017) are among the few economics studies that focus on WMPs. However, in both studies, all WMPs are lumped into just one variable. This study adds to the literature by achieving three objectives: (1) to describe the patterns of WMPs use by the sample producers in Arkansas, USA, (2) to identify the factors related to producers' choices of WMPs, and (3) to examine the correlations between WMPs use and irrigated acres. The data set used in this study has collected information on a large number of WMPs used by the sample producers on all of their fields. It allows us to study producers' choices regarding different groups of WMPs, with the recognition that these decisions are often interrelated. The study also provides insights on how producers combine different WMPs to manage multiple aspects of irrigation (e.g., water flow control, field management, water storage, and irrigation scheduling). As such, the study provides a more complete picture of producers' use of WMPs than depicted in previous studies that often only have data at the field level.

In the last decade or so, researchers have argued that although increasing irrigation efficiency often reduces the nonconsumptive loss of water such as evaporation during irrigation, that water saving does not necessarily translate into a reduction of total water use (e.g., Gómez & Pérez-Blanco, 2014). Pfeiffer and Lin (2014) are among the few studies on rebound effects that have used actual farm-level or field-level data instead of programming models and simulations (e.g., Hendricks & Peterson, 2012; Ward & Pulido-Velazquez, 2008). They find that when producers in western Kansas switched from center pivots to center pivots with dropped nozzles (higher efficiency) between 1995 and 2005, groundwater extraction increased. The rebound effect arose from two behavioral responses to the higher irrigation efficiency. Producers fallowed less frequently or irrigated more of their land. Producers also switched to water intensive crops such as corn, alfalfa, and soybeans, which resulted in a higher irrigation application rate per acre. Huang, Wang, et al. (2017), on the other hand, find that using water-saving technologies does not have statistically significant impacts on irrigated acres or crop mixes in North China. Therefore, the effects of more efficient irrigation vary by location. Although the study cannot directly estimate the rebound effect because the data are cross sectional, the analysis of correlations between WMPs use and irrigated acres sheds some light on potential unintended consequences of policies that target improving irrigation efficiency.

The organization of the rest of the paper is as follows. Section 2 introduces the study site and the data set. Section 3 describes irrigation practices used in Arkansas. Section 4 presents the empirical models, and section 5 reports estimation results. Section 6 concludes with policy implications from the research findings.

2. Study Site and Data Description

The study focuses on the state of Arkansas, USA. Agriculture is a key sector in Arkansas's economy. The main crops grown in the state are rice, soybean, corn, and cotton. Rice production in Arkansas now ranks first in the nation, accounting for almost half of total U.S. production (U.S. Department of Agriculture, 2016). Precipitation in Arkansas usually spikes between March and May and between October and December, while the growing seasons of most major crops are from April to September/October (Arkansas Natural Resources Commission, 2015). As a result, Arkansas's crop production relies heavily on irrigation. For example, almost all rice is irrigated. More and more soybean, corn, and cotton are irrigated, and the shares of irrigated acres for these crops reach 90% in some years (NASS, 2014). In 2007, Arkansas accounted for 7.9% of all cropland under irrigation in the United States, making the state the fourth largest user of irrigation water in the country (Schaible & Aillery, 2012).

More than 80% of irrigation water in Arkansas is groundwater pumped from the Mississippi River Valley Alluvial Aquifer (MRVAA, NASS, 2014; Schrader, 2008). Heavy pumping has put tremendous pressure on the MRVAA and caused concerns about the depletion of groundwater. Many counties in eastern Arkansas have been designated as critical groundwater areas because groundwater levels have dropped by 15 meters or more (Arkansas Soil and Water Conservation Commission, 2003). In 11 out of the 27 counties in the Arkansas part of the MRVAA, the depth to water decreased in recent years, partly due to above average precipitation during the irrigation season since 2011 that lowered groundwater withdrawals and increased recharges (Arkansas Nature Resources Commission 2019). However, the depth to water increased in the other 16 counties, most of which are heavy agricultural water users. The average decline in these counties is more than 0.61 meter between 2008 and 2018. Significant cones of depression have formed, and water has dropped to a depth of more than 36.6 meters below ground. A projected annual gap between the supply and the demand of groundwater could be as large as 10 billion cubic meters -in 2050, and most of the expected shortfall is attributed to agriculture (Arkansas Natural Resources Commission, 2015). To combat groundwater shortage, the 2014 Arkansas Water Plan Update identifies two critical initiatives: (1) adopting conservation measures to improve on-farm water use efficiency and (2) developing infrastructure-based solutions to convert from groundwater to surface water irrigation (Arkansas Natural Resources Commission, 2015). This study provides important policy analysis to address the first critical initiative, since using WMPs could raise on-farm irrigation efficiency but the potential of unintended consequences such as rebound effects should be assessed.

The main data set is the 2016 Arkansas Irrigation Survey conducted by the authors. The sample in the survey is randomly drawn from all commercial crop growers identified by Dun and Bradstreet records for the state of Arkansas. Of 3,712 producers that enumerators attempted to contact through phone calls, 624 contacts were eligible to complete the survey. The final sample includes 224 farm operators that completed the survey in its entirety. Figure 1 shows locations of the sample counties. The average share of irrigated land in rice in our sample (27.59%) is close to that in the 2012 Census of Agriculture (27.50%, Knapp et al., 2018). The share of irrigated land in soybean is slightly higher in our sample (52.47% vs. 49.19%, Knapp et al., 2018). This is likely because soybean acreage has been increasing in Arkansas, and our survey took place 4 years after the 2012 Census of Agriculture. These comparisons indicate that our sample is comparable to that of the Census.

The survey collected detailed information on irrigation practices employed by Arkansas producers including whether a producer used each WMP in 2015, when the producer started to use each WMP, and how many acres are under different WMPs in 2015. In addition, the survey also collected information about the reasons for using or not using a practice, which year and month the practice was first used, whether the practice has reduced pumping time, and whether family members, friends, or neighbor producers have used the practice in the past 10 years. Information on when a practice was first used is used to construct the dummy variable indicating whether a practice was used in 2010. County-level climate data come from the National Oceanic and Atmospheric Administration, National Climatic Data Center (2016), to calculate mean daily temperature and average annual precipitation in the previous 30 years.

3. The Use of WMPs in Arkansas

Table 1 reports irrigation technologies used by Arkansas producers in 2015. Four technologies are observed in the data: center pivot irrigation and three types of gravity irrigation (flood, border, and furrow irrigation). The majority of Arkansas producers (more than 70%) use two or more irrigation technologies on their farms. Most often, different irrigation technologies are used on different fields. Many producers (about 43%) use two different technologies. For example, the most commonly observed pattern is flood and furrow irrigation on the same farm (35%). Only 5.8% of the producers use center pivot exclusively on their farms. The remaining (94.2%) either use gravity irrigation (69.2%) or use both gravity and center pivot irrigation (25%). Since the unit of analysis of the study is at the farm level and almost all producers use gravity irrigation, it is difficult to analyze the joint choice of irrigation technologies and WMPs. Instead, this study analyzes the choices of WMPs conditional on irrigation technologies that are used on farm, which are measured by the percentage of irrigated acres under gravity irrigation.

The survey collected information on 16 WMPs. Table 2 provides detailed descriptions of these WMPs. WMPs are put in four groups based on which aspect of irrigation is being managed. Field management practices include zero-grade leveling, precision-grade leveling, end blocking, warped surface, and deep tillage. Water flow control practices include multiple-inlet irrigation, computerized pipe hole selection, surge irrigation, water flow meters, and cutback irrigation. Water recovery/storage practices include tailwater recovery systems and on-farm storage reservoirs. Advanced irrigation scheduling practices include soil moisture sensor, evapotranspiration (ET) or Atmometer, computerized scheduling, and woodruff chart. The most prevalent group of WMPs is field management practices. Nearly 85% of the producers use one or more WMPs in this group. The least prevalent group is advanced irrigation scheduling practices, which are used by only about 16% of the sample producers. One reason for the low percentage is that these practices come into use much later than WMPs in other groups.

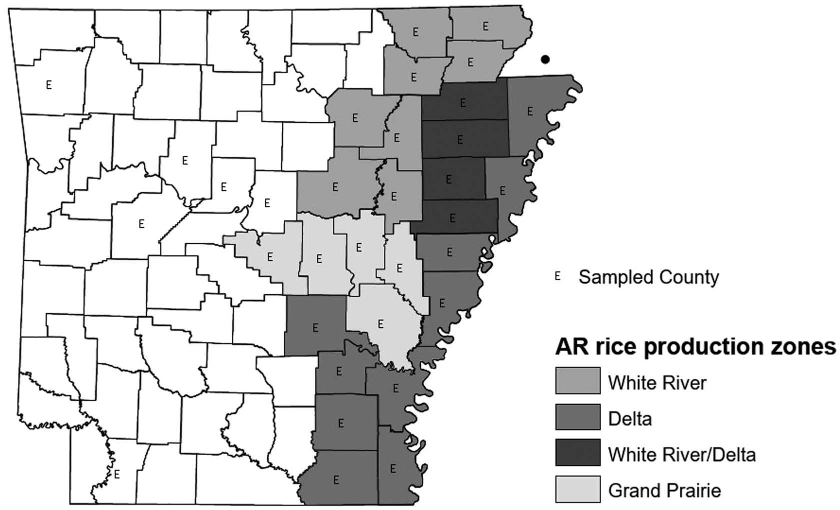

Figure 1. Locations of the sample counties of 2016 Arkansas Irrigation Survey and rice production zones in Arkansas.

Most producers in our sample use WMPs to manage more than one aspect of irrigation. About 77% of the producers use WMPs from two or more groups (Table 3). Similar shares of producers use two groups (34%) or three groups (35%) of WMPs. The share of producers who use all four groups drops sharply to only 8%. We also observe distinctive patterns in which groups are used together. Among producers that only use one group of WMPs, field management practices (10.3%) are the most common choice. Among producers that use two groups of WMPs, the most commonly observed pattern is the combination of field management and water flow practices (24.6%). Among producers that use three groups, the most common combination is field management, water flow control, and water recovery/storage practices (30%). These patterns reveal a possible hierarchy of WMPs: field management is first considered, and water flow control is the next in line before water recovery/storage is considered. Advanced irrigation scheduling comes in the last, again, probably due to its late arrival in the pool of available WMPs.

Observations on the use of individual WMPs are consistent with those on groups of WMPs. The majority of the producers (81.1%) use between one and six WMPs (Figure 2). Only 5.8% of the producers do not use any

Table 1
Irrigation Technologies Used by Arkansas Producers in 2015

N irrigation technologies	Flood irrigation[a]	Border irrigation[b]	Furrow irrigation[c]	Center pivot irrigation[d]	*N* producers	% Producers
4	Yes	Yes	Yes	Yes	17	7.59
3	Yes	Yes	Yes		26	11.61
	Yes		Yes	Yes	23	10.27
		Yes	Yes	Yes	1	0.45
2	Yes		Yes		79	35.27
			Yes	Yes	12	5.36
	Yes			Yes	2	0.89
	Yes	Yes			1	0.45
		Yes	Yes		1	0.45
		Yes		Yes	1	0.45
1			Yes		22	9.82
	Yes				15	6.70
				Yes	13	5.80
		Yes			11	4.91
				Total	224	100

[a]Flood irrigation covers an entire field with water. [b]Border irrigation uses raised beds or levees constructed in the field's slope and releases water into the area between the borders at the high end of the field. [c]Furrow irrigation is used on a field with a positive and continuous row grade. Furrows are dug between crop rows, and water is flown down the furrow with gravity. [d]Center pivot irrigation irrigates crops with sprinklers that rotate around a pivot.

Table 2
Water Management Practices (WMPs) Used by Arkansas Producers in 2015

Group	WMPs	Description	% Producers
Field management practices (84.38%)	Zero-grade leveling	A field is graded to a 0% level.[a]	18.30
	Precision-grade leveling	A field is graded to a specific slope.[a]	57.14
	Warped surface	A land leveling method where the grade is adjusted with a computer to get the best fit for the contour of the field, often with GPS enabled earthmoving equipment.[a]	25.89
	End blocking	Block the low end of furrows to keep tailwater on the field.[a]	30.80
	Deep tillage	Tillage operations below the normal tillage depth to modify adverse physical or chemical properties of a soil.[b]	47.32
Water flow control practices (67.41%)	Multiple-inlet irrigation (rice)	Gated pipes or holes placed on the pipe are used to deliver water to each paddy (area between levees). Each paddy is watered concurrently, instead of receiving overflow from a higher paddy.[a]	38.39
	Computerized pipe hole selection	A computer software application that assists producers in determining the sizes of the holes placed on the pipes that distribute water, often on furrow irrigated fields.[c]	31.70
	Surge irrigation	The surge valve oscillates water from one side of the valve to the other at decided time intervals and irrigates two lateral furrows intermittently and causes an intermittent wetting and soaking cycle in the irrigated furrows. By pulsing, or surging, water advances down the furrow faster, thus improving the uniformity of application.[c]	18.30
	Cutback irrigation	A method used to minimize runoff and improve water application efficiency by reducing water inflow rates to graded furrows after water reaches the lower end of the field.[a]	13.84
Water recovery/storage practices (50%)	Tailwater recovery system	A system used to collect, store and transport irrigation tailwater for reuse. Common components include pickup ditches, sumps, pits, pumps, and pipelines.[a]	45.54
	Storage reservoir	On-farm reservoirs constructed to capture and store surface water, often in stream runoff or rainwater, to be used for irrigation in crop growing seasons. Often used together with tailwater recovery systems.[a]	34.82
Advanced irrigation scheduling practices (15.63%)	Soil moisture sensor	Sensors used to measure soil moisture within crop root zone.[c]	9.38
	ET or Atmometer	A water-filled tube placed in the field. When the water level drops due to evaporation, markings on the tube provide on-site evapotranspiration (ET) information.[c]	3.13
	Computerized scheduling	The commonly used one in Arkansas is “Arkansas Online Irrigation Scheduler,” which uses the water balance approach to schedule irrigation. Both PC version and internet version are available.[c]	5.80
	Woodruff chart	A printed paper chart used to estimate soil moisture. Information on crop type, soil type, irrigation method, emergence date and number of days until relative maturity, historical ET, and rainfall events are used to draw the chart (Henggeler, 2009).[d]	1.34

[a]Henry, C., M. Daniels, M. Hamilton and J. Hardke. 2018. “Chap 10. Water Management.” In J. Hardke (ed) *Rice Production Handbook*. The University of Arkansas Division of Agriculture Cooperative Extension Service. [b]National Conservation Practice standards (https://www.nrcs.usda.gov/wps/portal/nrcs/detailfull/national/technical/cp/ncps/?cid=nrcs143_026849). Accessed 20 September 2019. [c]The University of Arkansas System Division of Agriculture. Irrigation for Agriculture in Arkansas (https://www.uaex.edu/environment-nature/water/irrigation.aspx). Accessed 20 September 2019. [d]Henggeler, J. 2009. Woodruff Irrigation Charts. In *Proceedings of World Environmental and Water Resources Conference*, S. Starrett, ed. Reston, VA: ASCE/EWRI.

WMPs. Within each group, some WMPs are more common than others. For example, precision-grade leveling (57.1%) and deep tillage (47.3%) are used more often than other field management practices (Table 2). Multiple-inlet irrigation is used by 38.4% of the producers. In contrast, less than 20% of the producers use either surge irrigation or cutback irrigation. Soil moisture sensors are used by more producers (9.4%) than ET or Atmometer (3.1%). The differences in the use rates may be because different WMPs have been in use for different lengths of time. For example, multiple-inlet irrigation was first in use as early as the 1950s, while the use of surge irrigation was only observed after the 1980s. This may explain why the current use rate of multiple-inlet irrigation is higher than that of surge irrigation.

4. Empirical Models

This section first presents the models for producers' patterns of WMPs use in section 4.1. A multivariate probit model is used for choices of which groups of WMPs to use. An ordered probit model is used for decisions on how many groups of WMPs to use. Section 4.2 explains the selection of explanatory variables

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Table 3
WMPs Use Patterns by Arkansas Producers in 2015

N groups	Field management	Water flow control	Water recovery/storage	Advanced irrigation scheduling	*N* producers	% Producers
4	Yes	Yes	Yes	Yes	18	8.04
3	Yes	Yes	Yes		67	29.91
	Yes	Yes		Yes	10	4.46
	Yes		Yes	Yes	2	0.89
2	Yes	Yes			55	24.55
	Yes		Yes		14	6.25
		Yes	Yes		6	2.38
		Yes		Yes	2	0.89
1	Yes				23	10.26
		Yes			6	2.68
			Yes		5	2.23
				Yes	3	1.34
0					13	5.80
				Total	224	100

in the empirical models. Section 4.3 presents the models that analyze correlations between WMPs use and irrigated acres.

4.1. Models for WMPs Use

In the economics literature, agricultural technology adoption decisions are often modeled using a random utility framework (McFadden, 1981). It can also be applied to model decisions on WMPs. A utility-maximizing producer i will use WMPs from a group g if the utility gained from using group g WMPs (U_{ig}) is greater than the utility of not using (U_{iNg}): $y^*_{ig} = U_{ig} - U_{iNg} > 0$. Since these utilities are unobservable, the net benefit (y^*_{ig}) that the producer derives from using group g WMPs is a latent variable and a function of observable characteristics $\mathbf{x}_{1i}$ and an error term ε_{ig}. We can observe a binary variable, y_{ig}, which indicates a producer i used group g WMPs. Using a single-equation model for each WMPs group separately may not be appropriate since the decision regarding one group of WMPs likely correlates with that regarding other groups. For example, many water flow control practices such as multiple-inlet irrigation work better on precision-graded land. Another example is that since soil moistures vary less on precision-graded fields, they can be more accurately measured even though sensors are often placed only at a few spots of the field. Therefore, a multivariate probit model is used to estimate the decisions regarding all four groups of WMPs simultaneously in a system of four equations (Greene, 2012).

$$\begin{aligned} &y^*_{ig} = \mathrm{x}1i\beta_g + \varepsilon_{ig} \\ &y_{ig} = 1 \mathrm{if}\ y^*_{ig}>0 \ \text{ and } y_{ig} = 0 \ \text{ otherwise} \qquad g = 1, 2, 3, 4. \end{aligned} \tag{1}$$

The random utility framework can also model a producer's decision regarding how many groups of WMPs to use. A producer will use n groups of WMPs if the net benefit of using WMPs, a continuous latent variable, is larger than π_{n-1} but smaller than π_n. If the net benefit is less than π_{n-1} or more than π_n, the producer will use fewer than or more than n groups. Both πs are cutoff points. The ordered probit model is a widely used model for such ordered choices. In the results section, we report the marginal effects of explanatory variables on the probability of using n groups of WMPs since they are easier to interpret. The marginal effects from the ordered probit model are as follows:

$$\begin{aligned} &\partial Pr(N_i = 0)/\partial \mathbf{x}_{2i} = -\phi\left(\mathbf{x}'_{2i}\boldsymbol{\lambda}\right)\boldsymbol{\lambda} \\ &\partial Pr(N_i = n)/\partial \mathbf{x}_{2i} = -\left[\phi\left(\pi_n - \mathbf{x}'_{2i}\boldsymbol{\lambda}\right) - \phi\left(\pi_{n-1} - \mathbf{x}'_{2i}\boldsymbol{\lambda}\right)\right]\boldsymbol{\lambda}, \quad n = 1, 2, 3. \\ &\partial Pr(N_i = 4)/\partial \mathbf{x}_{2i} = \phi\left(\pi_3 - \mathbf{x}'_{2i}\boldsymbol{\lambda}\right)\boldsymbol{\lambda} \end{aligned} \tag{2}$$

Since ϕ $(\cdot)$ is the standard normal probability distribution function and positive by definition, equation (2) shows that ∂Pr $(N_i = 0)/\partial \mathbf{x}_{2i}$ and Pr $(N_i = 4)/\partial \mathbf{x}_{2i}$ have opposite signs.

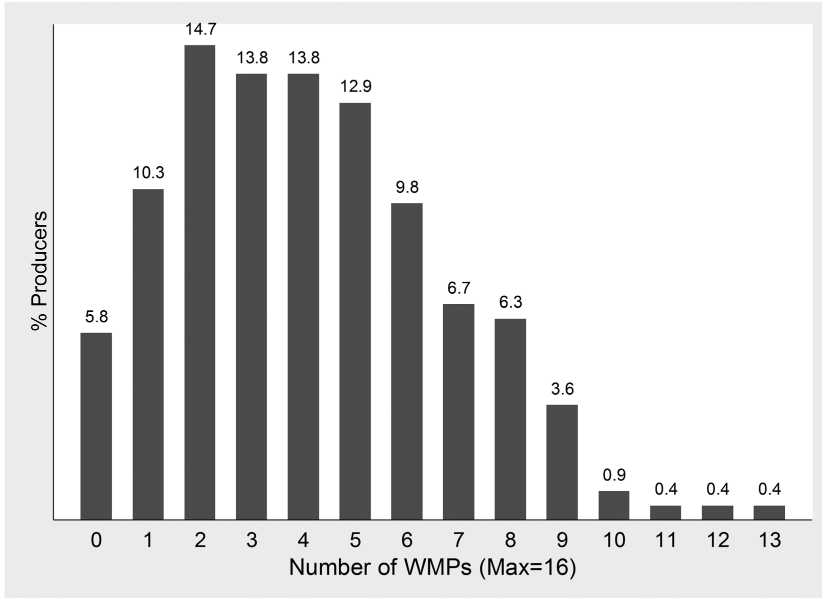

Figure 2. Number of water management practices used by Arkansas producers in 2015. *Source*: 2016 Arkansas Irrigation Survey.

4.2. Selection of Explanatory Variables

Consistent with the random utility framework, most explanatory variables in the empirical model would influence either costs or benefits of WMPs. Empirical literate on the adoption of irrigation technologies and best management practices also provide guidance on which variables to include. Five categories of explanatory variables are used. Table 4 reports the description and summary statistics of the variables.

The first category measures the characteristics of producers: dummy variables indicating if a producer is a land owner, has a bachelor or above degree or any part of the producer's formal education is related to agriculture, as well as continuous variables measuring years of farming experience, the level of household income, and the percentage of household income generated from farming activities. In the survey, producers were asked which category best described their 2014 household income from all sources before taxes. Answers are coded in the same set of intervals of income as in the Census of Agriculture: Less than \$10,000, \$10,000 to \$15,000, \$20,000 to \$25,000, \$25,000 to \$35,000, \$35,000 to \$50,000, \$50,000 to \$75,000, \$75,000 to \$100,000, \$100,000 to \$150,000, \$150,000 to \$200,000, \$200,000 to \$250,000, \$250,000 to \$300,000, and more than \$300,000. A producer's income is calculated as the middle point of the interval reported. For the lowest interval (less than \$10,000), since the width of the next two intervals are \$5,000 (\$10,000 to \$15,000, \$15,000 to \$20,000), the value of \$7,500 is used (\$10,000–\$5,000/2). For the highest interval, since the width of the previous four intervals is \$50,000, the value of \$325,000 is used.). In our sample, 82% of producers are land owners, while 18% of producers are only land operators (Table 4). On average, the sample producers have 33 years of farming experience, 51% have a bachelor's degree or above, and 56% of them have an agriculture-related education background. Land ownership increases benefits from irrigation investment since both short-term returns such as higher farm profits and long-term returns such as higher land values mostly accrue to land owners. Higher levels of education, especially if agriculture related, could help producers grasp the technical know-hows of WMPs more easily. Producers with more farming experience may be more familiar with WMPs that have been in use for a long time such as land leveling but may be less open to newer WMPs such as ET or Atmometer. Both Koundouri et al. (2006) and Olen et al. (2016) have found age, which is often highly correlated with farming experience, negatively correlates with the adoption of newer irrigation technology. Income can also influence WMPs use in multiple ways. Higher income may remove barriers to adopt WMPs such as liquidity constraints. Since higher income often increases the opportunity cost of producers' time, it may also provide incentives to adopt WMPs that can save labor inputs as well.

Table 4
Variable Description and Summary Statistics

Variable name	Description	Mean	Std. dev.	Min	Max
Water management practices (WMPs) variables					
Field2015	A producer used field management practices in 2015	0.84	0.36	0	1
Flow2015	A producer used water flow control practices in 2015	0.67	0.47	0	1
Storage2015	A producer used water recovery/storage practices in 2015	0.50	0.50	0	1
Scheduling2015	A producer used advanced irrigation scheduling practices in 2015	0.15	0.36	0	1
N_Group_WMP_2015	Number of groups of WMP used in 2015	2.23	1.01	0	4
Meter2015	Flow meters were installed on wells in 2015	0.34	0.47	0	1
Producer characteristics					
Land owner	A producer is land owner	0.82	0.39	0	1
Bachelor or above	A producers' highest degree is Bachelor or above	0.51	0.50	0	1
Ag_Edu	A producer has an agriculture-related education background	0.56	0.50	0	1
Yrs_Farm	Total years of farming experience	32.82	15.74	1	73
Income	Household income ($1,000)	127.91	94.84	7.5	325
% Farm_Inc	% household income generated from farming activities	0.82	0.26	0.05	1
Farm characteristics					
Tir_Acres	Total irrigated acres in 2015 (1,000 acres)	2.62	2.64	0.035	20.05
Ir_Acres_Rice	Total irrigated rice acres in 2015 (1,000 acres)	0.73	0.98	0	6.25
Ir_Acres_Soybean	Total irrigated soybean acres in 2015 (1,000 acres)	1.33	1.46	0	12
Ir_Acres_Corn	Total irrigated corn acres in 2015 (1,000 acres)	0.35	0.97	0	10
% Gravity	% irrigated acres under gravity irrigation in 2015	0.89	0.24	0	1
% Groundwater	% irrigation water from groundwater	0.75	0.33	0	1
Conservation variables					
Shortage_Concern	A producer is concerned water shortage may occur in Arkansas in the next 10 years	0.70	0.46	0	1
Tax_Credit	A producer is aware of a state tax credits program that allows producers to claim up to $9,000 tax credits for conversions to surface water or land leveling	0.46	0.50	0	1
% Cons_Prog	% producers in the county that have participated in any federal, state, or local conservation programs in the last 5 years	0.43	0.20	0	1
Peer_Field	Family members, friends, or neighbors used field management WMPs	0.92	0.28	0	1
Peer_Flow	Family members, friends, or neighbors used water flow control WMPs	0.87	0.34	0	1
Peer_Storage	Family members, friends, or neighbors used water recovery/storage WMPs	0.71	0.46	0	1
Peer_Scheduling	Family members, friends, or neighbors used advanced irrigation scheduling	0.49	0.50	0	1
Peer_Pivot	Family members, friends, or neighbors used center pivot irrigation	0.67	0.47	0	1
Weather variables					
Temp30	Mean daily temperature in the previous 30 years (°F)	73.69	1.13	71.13	76.15
Rainfall30	Average annual precipitation in the previous 30 years (in.)	22.27	1.66	20.66	26.36
Farm location					
White River	Farm is located in the upper White River Valley of Arkansas	0.41	0.49	0	1
Delta	Farm is located in the Delta zone of Arkansas	0.33	0.47	0	1
Observations		224			

The second category of explanatory variables measures farm characteristics: total irrigated acres, the percentage of irrigated acres that use gravity irrigation, the percentage of irrigation water that is groundwater, and whether flow meters are installed on wells. The average irrigated acres are 10.5 square kilometers (Table 4). There are three main rice production zones in Arkansas (Tseng et al., 2013): the Upper White River Valley of Arkansas (White River) and Delta and Grand Prairie zones (Figure 1). Water supplies in the Delta zone are generally abundant and of good quality. Water supplies in the White River zone are relatively scarce. Two dummy variables are used to indicate a producer's location: one for the White River and the other for the Delta zones. Previous studies have found that the size of land (e.g., field size and farm size) plays an important role in the adoption of irrigation technologies (e.g., Green et al., 1996). Farms with more irrigated acres may benefit from economies of scale in that the fixed costs of using a WMP is spread over more acres. Since field management and water flow control WMPs improve the performance of gravity irrigation, farmers with more gravity irrigated land may benefit more from using WMPs. Since tailwater recovery systems collect irrigation runoff, they are usually used on fields with gravity irrigation. Sources of irrigation water supply (groundwater or surface water) affect the benefits of some WMPs. For example, tailwater recovery systems and on-farm storage reservoirs redistribute water temporally. Farms that

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irrigate mostly with groundwater, which is available year-around, would benefit much less from such temporal redistribution mechanisms.

The third category includes two variables: a dummy variable indicating that a producer is concerned water shortage that may occur in the state in the next 10 years and a dummy variable indicating that the producer is aware of the state tax credits program that allows producers to claim up to $9,000 tax credits for conversions to surface water or land leveling. Since WMPs supposedly alleviate water shortage problems, producers' perception of water shortage may influence their decisions to use WMPs. Government programs such as tax credits incentivize producers to use WMPs by lowering the costs of adoption.

The fourth category measures peer conservation efforts and peer use of WMPs: the percentage of producers in the county that have participated in any federal, state, or local conservation programs in the last 5 years and whether anyone in a producer's close network (family members, friends, or neighbors) has used the WMPs included in the survey. Previous literature has shown that producers' social networks cast a large influence on their decisions regarding irrigation. The meta-analysis by Baumgart-Getz et al. (2012) finds that local networks have relatively large impacts on producers' adoption of best management practices. Genius et al. (2013) suggest that producers likely learn about the existence and effective use of new practices from their social interaction with other producers. The peer use of WMPs variables is excluded from the ordered probit model because the survey did not collect information on the average number of WMP groups used by peer producers.

The fifth category includes two weather variables: county-level mean daily temperature and average total annual precipitation in the previous 30 years. Previous studies have found that producers adopt irrigation technologies such as sprinkler irrigation in order to lower production risks brought by increasingly volatile climate and extreme weather events such as droughts (e.g., Olen et al., 2016). Knapp and Huang (2017) have found that climatic factors can influence producers' water conservation behavior.

One variable of particular interest is the use of water flow meters since the state recommends it as a strategy to address groundwater declines in Arkansas (Arkansas Natural Resources Commission, 2015). It is also promoted to producers as a valuable water management tool for evaluating current irrigation practices, improving irrigation efficiency, determining pump efficiency, and detecting pump and irrigation system problems (Henry, 2012). For example, knowing the total amount of water pumped can help producers determine whether the correct amount of water has been applied to meet crop water demand and better schedule irrigation. Using flow meters to track water use before and after a WMP is used tells a producer the water savings the WMP has achieved. By tracking fuel use and water flow rate, a producer can determine the engine speed that provides the most water with the least amount of fuel to optimize pumping during the irrigation season.

4.3. Correlations Between WMP Uses and Irrigated Acres

The second part of the analysis investigates the correlations between WMPs use and producers' irrigated acres. This is a topic of particular importance to Arkansas. The Census of Agriculture data show that although total irrigated acres in the United States declined by 3,157 square kilometers from 2007 to 2012, Arkansas experienced the largest net gain during this period (1,388 square kilometers, USDA, National Agricultural Statistics Service 2012). Such an upward trend has been taking place in the state for several decades and continues to put more pressure on groundwater resources. Finding the factors related to the continuous increases in irrigated acres can help policymakers better manage water resources in the state. The estimating equation is as follows:

$$A_{im} = \mathbf{WMP}_i \theta_m + \mathbf{x}'_{3i} \eta_m + v_{im} \tag{3}$$

The dependent variable, A_{jm}, is indexed m to indicate which of producer i's irrigated acres is used: total irrigated acres on farm, irrigated acres in rice, irrigated acres in soybean, and irrigated acres in corn. To increase the estimation efficiency, all four equations are estimated together using Seemingly Unrelated Regressions (SUR).

The key variables of interest, $\mathbf{WMP}_i$, measure the use of WMPs by producer i. The first specification of $\mathbf{WMP}_i$ uses a set of dummy variables indicating which groups of WMPs were used in 2015. The second specification is an integer variable indicating how many groups of WMPs were used in 2015. A third specification that includes the set of dummy variables as well as the integer variable suffers from the multicollinearity problem. This is because of the distinctive patterns observed in Table 3: Using four groups of WMPs is highly collinear with using advanced scheduling practices, using three groups of WMPs is highly collinear with using water recovery/storage practices, and using two groups is highly collinear with using water flow control practices.

Variables in $\mathbf{WMP}_i$ may be endogenous because a producer who plans to increase irrigated acres may decide to use more WMPs to free up water. For similar reasons, the use of water flow meters and the percentage of gravity irrigated acres variable may be endogenous too. To address the potential endogeneity, instrumental variables (IVs) estimation is used. The following variables are potential IVs: a set of dummy variables indicating whether a producer's close network (family members, friends, or neighbors) used WMPs in the same group, a set of dummy variables indicating if a producer used WMPs in the same group in 2010, a dummy variable indicating whether the producer's close network installed water flow meters, county-level average percentage of gravity irrigated acres among other producers, a dummy variable indicating whether the producer is aware of the state tax credits, and the percentage of producers in the county that have participated in any government conservation programs in the last 5 years. These variables are likely to influence producers' choices of WMPs and irrigation technologies, but they are not likely to directly affect the dependent variables (irrigated acres). The Sargan (score) test statistics show that all IVs are valid (Sargan, 1958). Some of the IVs are explanatory variables in $\mathbf{x}_{1i}$ but are removed from $\mathbf{x}_{3i}$. The total irrigated acres variable is also removed since it is now the dependent variable.

Another important outcome is total water used on farm or more importantly consumptive water use. However, during the survey, we did not collect information on water use because producers were likely to be resistant to reporting their water use (The University of Arkansas Rice Research Verification Program (RRVP) recorded water use on program fields since the program started in 1983 with some interruption between 1991 and 2002 (Henry et al., 2016). However, water use was only measured on the fields enrolled in the RRVP. Addressing our research questions calls for the total amount of water used at the farm level or more importantly the total consumptive water use. Only a small number of fields, between 15 and 25, were included in the RRVP annually. In addition, since irrigation is not a primary focus of the RRVP, the only WMP information collected was the types of irrigation systems (contour levee, straight levee, multiple inlet, and zero grade). Therefore, the RRVP water use data are not included in the study.). Nonetheless, since a large part of the unintended consequence of higher irrigation efficiency works through the expansion of irrigated acres, our analysis still provides important insights.

5. Estimation Results

This section reports three sets of estimation results. Section 5.1 reports the results of the multivariate probit model that identifies factors related to a producer's decisions on which groups of WMPs to use. Section 5.2 reports the results of the ordered probit model that identifies factors related to a producer's decision on how many groups of WMPs to use. Section 5.3 reports the results of SUR as well as 3SLS models that examine the correlations between irrigated acres and WMPs use. Even though many factors are included in the empirical analysis, some factors may still be omitted due to the lack of data but are correlated both with the dependent variables (WMPs uses and irrigated acres) and the explanatory variables. Two such factors are land quality and technology-specific characteristics such as the installation, operation, and maintenance costs. Given that our data set is cross sectional in nature, panel data methods could not be used to control for all time invariant factors. Therefore, results presented in this section are based on associational relationships and may not support causal claims.

5.1. Factors Related to Which Groups of WMPs Are Used

Table 5 reports the results of estimating equation (1) using the STATA program mvprobit (Cappellari & Jenkins, 2003). The Wald test rejects the null hypothesis that all regression coefficients are jointly zero with a p-value of almost zero. The likelihood ratio test rejects the null hypothesis of zero correlations among error terms with a p-value of almost zero. Error term correlations are reported at the bottom of Table 5. A positive and statistically significant correlation exists between error terms of the field management equation and the water flow control equation, suggesting that producers tend to use these two groups of WMPs together. This

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Table 5
Multivariate Probit Model of Choices Among Groups of WMPs

	Field management	Water flow control	Water recovery/storage	Advanced irrigation scheduling
Land owner	−0.00936	−0.360	0.0250	0.181
	(0.283)	(0.273)	(0.304)	(0.289)
Bachelor or above	0.144	0.184	−0.171	0.206
	(0.252)	(0.221)	(0.243)	(0.224)
Ag_Edu	−0.149	0.301	−0.147	0.275
	(0.256)	(0.210)	(0.218)	(0.240)
Yrs_Farm	−0.000262	−0.0106	−0.00535	−0.0214***
	(0.00816)	(0.00737)	(0.00724)	(0.00812)
Income	0.00241*	0.000626	−0.000460	0.00303***
	(0.00143)	(0.00103)	(0.00111)	(0.00111)
% Farm_Inc	0.282	0.516	−0.0643	0.00647
	(0.447)	(0.414)	(0.416)	(0.511)
Tir_Acres	0.258***	0.180***	0.0431	0.0134
	(0.0873)	(0.0602)	(0.0549)	(0.0503)
% Gravity	0.745*	0.570	0.799	−0.506
	(0.453)	(0.438)	(0.542)	(0.496)
% Groundwater	0.371	0.0198	−1.635***	0.167
	(0.371)	(0.340)	(0.422)	(0.422)
Meter2015	0.153	0.263	0.526**	0.241
	(0.311)	(0.243)	(0.249)	(0.249)
Shortage_Concern	0.695***	0.180	0.0650	−0.101
	(0.244)	(0.237)	(0.247)	(0.265)
Tax_Credit	0.185	0.275	−0.0422	0.732***
	(0.245)	(0.202)	(0.217)	(0.246)
% Cons_Prog	1.025*	−0.0251	0.350	−0.0694
	(0.564)	(0.557)	(0.582)	(0.749)
Peer_Flow/Storage/Field/Scheduling	0.388	0.545*	1.646***	0.705***
	(0.327)	(0.296)	(0.273)	(0.248)
Temp30	−0.279**	−0.131	0.190	−0.0140
	(0.138)	(0.120)	(0.134)	(0.138)
Rinfall30	0.131*	−0.0295	−0.0406	0.119
	(0.0770)	(0.0631)	(0.0736)	(0.0748)
White River	−0.392	−0.167	−0.284	−0.307
	(0.305)	(0.276)	(0.280)	(0.314)
Delta	−0.382	−0.399	−0.819***	−0.211
	(0.310)	(0.324)	(0.314)	(0.346)
Constant	15.67	9.168	−13.46	−3.158
	(9.534)	(8.331)	(9.180)	(9.352)
p-value of Wald test		0.0000***		
Log pseudolikelihood		−357.512		
Correlation matrix of error terms¶				
Field management	1	0.305**	0.0165	0.0399
Water flow control		1	−0.117	0.144
Water recovery/storage			1	0.110

Note: Robust standard errors are reported in parentheses. The *p*-value of the Likelihood ratio test that all cross-equation correlations are jointly zero is 0.0187.
*Statistical significance at 10%. **Statistical significance at 5%. ***Statistical significance at 1%.

finding is in agreement with the agronomic recommendation that appropriate field management could improve the performance of water flow control practices. For example, agronomic experiments suggest that multiple-inlet irrigation is more easily managed on precision-graded fields (Henry et al., 2013).

Since our sample is only 224, the estimation of the multivariate probit model may be subject to the finite sample bias. An alternative is to estimate a separate probit model for each group of WMPs. The Monte Carlo experiment in Griffiths et al. (1987) shows that the sizes of the finite sample bias of probit model

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estimates are reduced significantly when the sample size reaches 100. For example, for a parameter with a true value of 0.9633, the size of the bias decreases from 0.122 to 0.054 when the sample size increases from 50 to 100. The comparison between the multivariate probit model estimates (Table 5) and the separate probit model estimates (Appendix A) shows that most coefficients are close in magnitudes with negligible differences. Therefore, we believe that the finite sample bias may be present in Table 5 results, but the magnitudes may not be large enough to cause concerns.

Table 5 reports the estimates of $\boldsymbol{\beta}_g$ in equation (1). In probit models, the signs of $\boldsymbol{\beta}_g$ would be the same as the signs of marginal effects of the same explanatory variable. Therefore, we focus only on the signs and levels of statistical significance of coefficients. A positive (negative) coefficient indicates a positive (negative) correlation between an explanatory variable and the dependent variable. No statistically significant correlations are found between the use of WMPs and land ownership or producers' education. A negative correlation is found between years of farming experience and the use of advanced irrigation scheduling practices. Since years of farming experience is closely related to age, and older producers may be less exposed to new technologies, this may explain why newer WMPs, such as advanced irrigation scheduling practices, are used less by producers with more farming experience. The coefficients of household income are statistically significant in some equations but are close to zero in magnitudes so bear little practical significance.

Among the farm characteristics variables, the coefficients of total irrigated acres are positive in all four equations. They are larger in magnitudes and statistically significant in the field management and water flow control equations. The positive correlations make sense since larger farms likely require more land management. Since water flows are more difficult to manage on larger farms, these farms may also benefit more from practices such as multiple-inlet irrigation and surge irrigation that increase the uniformity of irrigation application. The percentage of irrigation water from groundwater negatively correlates with the use of water recovery and/or storage practices. One possible explanation is that groundwater varies much less seasonally than surface water; producers that draw more of their irrigation water from aquifers have less need for tailwater recovery systems or storage reservoirs to store water for future use (Huang, Xu, et al., 2017). A positive and statistically significant correlation is observed between the use of flow meters and the use of tailwater recovery systems and/or storage reservoirs. It is possible that decreases in water yields in wells are more easily detected when flow meters are installed, which may lead to the decision of augmenting water supplies on farm using tailwater recovery systems and/or on-farm reservoirs. Information provided by flow meters can also help producers decide when to pump the stored water from reservoirs to put back on their farms.

A positive and statistically significant correlation is observed between concerns of water shortage in the state in the next 10 years and the use of field management practices. A positive and statistically significant correlation is observed between the percentage of farmers that have participated in government programs in the past 5 years and the use of field management practices. No statistically significant correlations are found between the awareness of the state tax credits and the use of field management or water recovery/storage practices. This is puzzling because the tax credits provide financial assistance for the adoption of these two groups of practices. Instead, it has a positive and statistically significant correlation with the use of advanced irrigation scheduling practices. One possible explanation for the positive correlation is that data collected on irrigation scheduling devices such as soil moisture sensors better represent soil moistures of the whole field if it is precision graded. The WMPs use of a producer's close network (family members, friends, or neighbors) positively correlates with the producer's WMPs use. The correlations are statistically significant except for field management practices. This is consistent with findings from a large existing literature that information sharing and social learning through close network plays a central role in the diffusion of agricultural technologies (e.g., Conley & Udry, 2010).

5.2. Factors Related to How Many Groups of WMPs Are Used

Table 6 reports the average marginal effect of an explanatory variable on the probability of using n groups of WMPs ($n = 0$, 1, 2, 3, or 4). Using the estimation results of the ordered probit model, the marginal effect is computed for each observation and then the average across all observations is reported. All other things equal, a one unit change in the explanatory variable is associated with an increase or decrease in the predicted probability equal to the size of the marginal effect. For each explanatory variable, the signs are the same in the first three columns. The signs are also the same in the last two columns. In addition, the signs of the first three columns (use zero, one, or two groups of WMPs) and those of the last two columns (use

Table 6
Ordered Probit Model of the Number of Groups of WMPs Average Marginal Effects

	0	1	2	3	4
Land owner	0.00729	0.0113	0.00425	−0. 0147	−0.00812
	(0.0214)	(0.0333)	(0.0127)	(0.0432)	(0.0241)
Bachelor or above	−0.0157	−0.0244	−0.00917	0.0318	0.0175
	(0.0163)	(0.0254)	(0.0107)	(0.0330)	(0.0189)
Ag_Edu	−0.0151	−0.0234	−0.00879	0.0305	0.0168
	(0.0149)	(0.0234)	(0.00894)	(0.0301)	(0.0167)
Yrs_Farm	0.00101*	0.00157**	0.000590*	−0.00205**	−0.00113*
	(0.000547)	(0.000757)	(0.000342)	(0.000981)	(0.000599)
Income	−0.000171**	−0.000265**	−0.0000997*	0.000346**	0.000190**
	(0.0000850)	(0.000126)	(0.0000569)	(0.000162)	(0.0000940)
% Farm_Inc	−0.0502	−0.0778	−0.0292	0.101	0.0558
	(0.0360)	(0.0513)	(0.0225)	(0.0688)	(0.0387)
Tir_Acres	−0.00929***	−0.0144***	−0.00541**	0.0188***	0.0103***
	(0.00310)	(0.00474)	(0.00220)	(0.00573)	(0.00338)
% Gravity	−0.0753**	−0.117**	−0.0439*	0.152**	0.0838**
	(0.0323)	(0.0486)	(0.0254)	(0.0658)	(0.0355)
% Groundwater	0.0586**	0.0909**	0.0341*	−0.118**	−0.0652**
	(0.0288)	(0.0393)	(0.0188)	(0.0506)	(0.0321)
Meter2015	−0.0367*	−0.0569*	−0.0214*	0.0742**	0.0408**
	(0.0192)	(0.0292)	(0.0113)	(0.0372)	(0.0199)
Shortage_Concern	−0.0397**	−0.0616**	−0.0231**	0.0803**	0.0442**
	(0.0198)	(0.0262)	(0.0112)	(0.0336)	(0.0205)
Tax_Credit	−0.0415**	−0.0643***	−0.0242**	0.0838***	0.0461**
	(0.0174)	(0.0229)	(0.0111)	(0.0290)	(0.0188)
% Cons_Prog	−0.0488	−0.0758	−0.0285	0.0987	0.0544
	(0.0471)	(0.0711)	(0.0276)	(0.0921)	(0.0519)
Temp30	0.00652	0.0101	0.00380	−0.0132	−0.00725
	(0.00947)	(0.0138)	(0.00531)	(0.0184)	(0.0101)
Rainfall30	−0.00556	−0.00863	−0.00324	0.0112	0.00619
	(0.00531)	(0.00760)	(0.00309)	(0.0101)	(0.00572)
White River	0.0365*	0.0567*	0.0213*	−0.0739*	−0.0407*
	(0.0212)	(0.0297)	(0.0125)	(0.0396)	(0.0215)
Delta	0.0640***	0.0993***	0.0373**	−0.129***	−0.0712***
	(0.0235)	(0.0355)	(0.0171)	(0.0448)	(0.0257)
p-value of Wald test		0.0000***			
Log pseudolikelihood		−271.63			

Note. Robust standard errors are reported in parentheses.
*Statistical significance at 10%. **Statistical significance at 5%. ***Statistical significance at 1%.

three or four groups of WMPs) are the opposite. This is because the marginal effects of the same explanatory variable across the five WMP categories must sum to zero by definition, as shown in equation (2).

More farming experience is associated with higher probabilities of using zero, one, or two groups of WMPs and lower probabilities of using three or four groups of WMPs. Older producers may not be as motivated to save water because they are near retirement. They may also have less energy to manage more groups of WMPs. Higher household income and more irrigated acres are associated with higher probabilities of using three or four groups of WMPs and lower probabilities of using zero, one, or two groups of WMPs. In addition to economies of scales, it is also possible that producers with higher household income and/or larger farms have access to more capital to invest in WMPs or hire professional farm managers and thus are more capable of practicing more groups of WMPs. This is consistent with the findings of previous studies that producers with larger farms make more conservation efforts (e.g., Schuck et al., 2005; Tosakana et al., 2010). Higher shares of gravity irrigated acres are associated with higher probabilities of using three or four groups of WMPs and lower probabilities of using zero, one, or two groups of WMPs. This makes sense since WMPs such as multiple-inlet, zero, or precision-grade leveling and tailwater recovery/storage reservoirs are often used on fields with gravity irrigation.

A larger percentage groundwater for irrigation is associated with higher probabilities of using zero, one, or two groups of WMPs and lower probabilities of using three or four groups of WMPs. Since groundwater is a relatively more reliable source of irrigation water, producers who rely more heavily on groundwater have fewer incentives to save water (Huang, Xu, et al., 2017). Using water flow meters is associated with higher probabilities of using three or four groups of WMPs. This may be because flow meters can increase the effectiveness of multiple WMPs by providing information on water flow rates and total water pumped. For example, good irrigation scheduling practices require knowing how much water is applied to each field, which is measured by water flow meters. Concerns of water shortages in the state and the awareness of the state tax credits are associated with higher probabilities of using three or four groups of WMPs.

Several alternative specifications are run to check the robustness of the results. In all tables, we report estimation results of the main specifications where the use of water flow meters is taken out of the water flow control group and used as a separate explanatory variable. We also run alternative specifications where the use of water flow meters stays in the water flow control group (reported in Tables S1 and S2 in the supporting information). The estimation results on other explanatory variables are largely consistent between the main specifications and the alternative specifications in terms of signs, levels of statistical significance, and magnitudes of coefficients. One difference is that in the multivariate probit model, the correlation between the error terms of the water flow control and advanced irrigation scheduling equations is much larger in magnitude and statistically significant in the alternative specification. Since the choices of WMPs correlate with crop choices, a version of equations (1) and (2) that includes the percentages of irrigated acres in rice, soybean, and corn as explanatory variables is also estimated (reported in Tables S3 and S4). The inclusions of these variables did not affect the estimation results on most other explanatory variables. In both multivariate probit and order probit models, the coefficients of the percentage of gravity irrigated acres variable lose statistical significance in the field management equation. Instead, the coefficient of the percentage of irrigated acres in rice variable is large and statistically significant. Since the use of WMPs may affect the size of irrigated acres, we also estimate a version of equations (1) and (2) that excludes total irrigated acres (reported in Tables S5 and S6). The results remain largely the same. One difference is that coefficients of the variable that measures the percentage of income generated from farming activities are now larger and statistically significant in the multivariate probit and order probit models. This change makes sense since the percentage of income from farming is likely to be positively correlated with the size of irrigated acres.

5.3. Correlations Between WMPs Use and Irrigated Acres

Results of estimating equation (3) using SUR show that the coefficients of several variables that measure WMPs use in 2015 are positive and statistically significant. We refrain from making causal claims and interpret a positive (negative) coefficient as indicating a positive (negative) correlation between the explanatory variable and irrigated acres in 2015. Using field management practices, water flow control practices or water flow meters positively correlate with total irrigated acres in 2015 (Table 7, Column 1). Using field management practices positively correlates with irrigated acres in rice and irrigated acres in soybean (Columns 2 and 3). Using tailwater recovery systems and/or on-farm reservoirs positively correlates with irrigated acres in corn (Column 4). Using water meters positively correlates with irrigated acres in rice and irrigated acres in soybean (Columns 2 and 3). When 3SLS is used, only the coefficients of water flow meters remain statistically significant in total irrigated acres, rice irrigated acres, and soybean irrigated acres equations (C5–7). The loss of statistical significance may be due to weak instruments. Except for the use of tailwater recovery systems and/or on-farm reservoirs, the first stage F statistics for most endogenous variables are lower than 10, indicating possibilities of weak instruments (Stock & Yogo, 2005). The weak instrument minimum eigenvalue test statistics developed by Cragg and Donald (1993) also confirm the weak instruments problem.

Table 8 reports the estimation results when the number of groups of WMPs used is the key variable of interest. When SUR is used, the coefficients of the number of groups of WMPs used are positive and statistically significant in total irrigated acres, rice irrigated acres, and soybean irrigated acres equations (Table 8, Columns 1–3). The coefficients of water meters are positive and statistically significant in total irrigated acres and soybean irrigated acres equations (columns 1 and 3). When 3SLS is used, the coefficients of the number of groups of WMPs used turn negative in total irrigated acres, rice irrigated acres, and soybean irrigated acres equations (Columns 5–7). The coefficient is only statistically significant in soybean irrigated acres equation

Table 7
Regressions of 2015 Irrigated Acres (1,000 acres) on 2015 Use of WMPs

	Seemingly unrelated regressions				Three-stage least squares[a]			
	(1) Total	(2) Rice	(3) Soybean	(4) Corn	(5) Total	(6) Rice	(7) Soybean	(8) Corn
Field2015[a]	0.917**	0.410**	0.513*	0.120	0.417	0.235	−0.0812	0.618
	(0.467)	(0.174)	(0.262)	(0.184)	(2.103)	(0.666)	(1.188)	(0.633)
Flow2015[a]	0.696*	0.155	0.259	0.199	−0.151	0.0423	−0.424	0.264
	(0.370)	(0.138)	(0.207)	(0.146)	(1.333)	(0.422)	(0.753)	(0.402)
Storage2015[a]	0.379	0.153	−0.0836	0.398***	−0.956	0.0322	−0.693	−0.0149
	(0.371)	(0.138)	(0.208)	(0.146)	(0.815)	(0.258)	(0.460)	(0.245)
Scheduling2015[a]	0.203	0.169	0.293	−0.236	−0.223	−0.198	−0.570	0.523
	(0.447)	(0.166)	(0.250)	(0.176)	(1.703)	(0.539)	(0.962)	(0.513)
Meter2015[a]	1.019***	0.282**	0.579***	−0.0580	4.978***	1.242***	3.013***	−0.166
	(0.369)	(0.137)	(0.207)	(0.145)	(1.447)	(0.458)	(0.817)	(0.436)
Land owner	0.283	−0.200	0.0819	0.230	0.478	−0.124	0.230	0.168
	(0.441)	(0.164)	(0.247)	(0.174)	(0.644)	(0.204)	(0.364)	(0.194)
Bachelor or above	0.441	0.219*	0.121	0.0646	0.100	0.135	−0.0329	0.0227
	(0.349)	(0.130)	(0.196)	(0.137)	(0.512)	(0.162)	(0.289)	(0.154)
Ag_Edu	−0.498	−0.131	−0.213	−0.0359	−0.907*	−0.228	−0.412	−0.0684
	(0.338)	(0.126)	(0.190)	(0.133)	(0.523)	(0.166)	(0.295)	(0.158)
Yrs_Farm	−0.0304***	−0.00235	−0.0145**	−0.00893**	−0.0410**	−0.00579	−0.0237**	−0.00581
	(0.0112)	(0.00417)	(0.00627)	(0.00441)	(0.0191)	(0.00605)	(0.0108)	(0.00575)
Income	−0.000894	−0.000961	−0.000699	0.0000480	−0.000885	−0.000777	−0.0000832	−0.000761
	(0.00172)	(0.000642)	(0.000966)	(0.000679)	(0.00281)	(0.000891)	(0.00159)	(0.000848)
% Farm_Inc	2.384***	0.727***	1.083***	0.327	3.256***	0.939**	1.627**	0.315
	(0.641)	(0.239)	(0.359)	(0.252)	(1.237)	(0.391)	(0.698)	(0.373)
% Gravity[a]	0.0759	0.588**	−0.454	−0.0394	7.182*	2.347*	2.999	0.849
	(0.722)	(0.269)	(0.404)	(0.284)	(3.845)	(1.217)	(2.172)	(1.158)
% Groundwater	0.799	−0.107	0.397	0.323	2.060**	0.340	1.187**	0.136
	(0.563)	(0.209)	(0.315)	(0.221)	(0.981)	(0.310)	(0.554)	(0.295)
Shortage_Concern	−0.362	−0.0404	0.0644	−0.368***	−0.848	−0.171	−0.0994	−0.508***
	(0.362)	(0.135)	(0.203)	(0.142)	(0.547)	(0.173)	(0.309)	(0.165)
Temp30	0.0473	−0.143**	0.0664	0.150**	−0.337	−0.258**	−0.158	0.164
	(0.190)	(0.0706)	(0.106)	(0.0746)	(0.345)	(0.109)	(0.195)	(0.104)
Rainfall30	−0.109	−0.00852	−0.0856	−0.00302	0.121	0.0583	0.0558	−0.0185
	(0.109)	(0.0406)	(0.0612)	(0.0430)	(0.188)	(0.0597)	(0.106)	(0.0568)
White River	0.749*	0.428***	0.325	−0.128	1.371**	0.576***	0.693*	−0.147
	(0.421)	(0.157)	(0.236)	(0.165)	(0.669)	(0.212)	(0.378)	(0.201)
Delta	1.233**	0.309	0.588**	−0.0699	2.390***	0.667***	1.202***	−0.0620
	(0.507)	(0.189)	(0.284)	(0.200)	(0.792)	(0.251)	(0.447)	(0.239)
Constant	−2.407	9.827**	−3.061	−11.10**	13.45	14.77**	6.815	−12.53*
	(13.08)	(4.870)	(7.327)	(5.146)	(21.90)	(6.932)	(12.37)	(6.597)
R^2	0.2432	0.2369	0.2207	0.1290				
p-value of Wald test	0.0000***	0.0000***	0.0000***	0.0159**	0.0000***	0.0000***	0.0000***	0.0611*

Note. Standard errors reported in parentheses.
[a]In Columns 5–8, instrumental variables (IVs) for these endogenous variables include the following: peers (family members, friends, or neighbors) used the same group of WMPs, the producer used the same group of WMPs in 2010, peers (family members, friends, or neighbors) used flow meters, average percentage of gravity irrigated acres among other producers, aware of the state tax credits, and percentage of producers in the county that have participated in any federal, state, or local conservation programs in the last 5 years. A multivariate probit model is first run with the endogenous dummy variables as the dependent variables. Explanatory variables include IVs and other explanatory variables in Table 7. The predicted probabilities from the multivariate probit model are then used as IVs in the 3SLS estimation. *Statistical significance at 10%. **Statistical significance at 5%. ***Statistical significance at 1%.

(Column 7). The coefficients of water meters are positive and statistically significant in total irrigated acres, rice irrigated acres, and soybean irrigated acres equations (Columns 5–7).

Although our analysis does not provide direct evidence on the rebound effects, it sheds light on potential unintended consequences of higher irrigation efficiency. Because the coefficients of most WMP variables lose their statistical significance in the IV estimation, we do not have robust findings on the relationships between any individual WMP group and irrigated acres. However, the results show that the use of water flow meters positively correlates with total irrigated acres, irrigated acres in rice, and irrigated acres in

Table 8
Regressions of 2015 Irrigated Acres (1,000 acres) on the Number of Groups of WMPs Used in 2015

	Seemingly unrelated regressions				Three-stage least squares[a]			
	(1) Total	(2) Rice	(3) Soybean	(4) Corn	(5) Total	(6) Rice	(7) Soybean	(8) Corn
N_Group_WMP_2015[a]	0.237***	0.114***	0.0937**	0.0363	−0.460	−0.0149	−0.319*	0.0192
	(0.0760)	(0.0279)	(0.0427)	(0.0305)	(0.346)	(0.0997)	(0.187)	(0.0896)
Meter2015[a]	0.956**	0.221	0.549***	−0.0308	6.069***	1.327***	3.536***	0.111
	(0.376)	(0.138)	(0.211)	(0.151)	(1.583)	(0.456)	(0.857)	(0.410)
Land owner	0.265	−0.197	0.100	0.195	0.586	−0.124	0.279	0.212
	(0.442)	(0.162)	(0.248)	(0.177)	(0.735)	(0.212)	(0.398)	(0.190)
Bachelor or above	0.457	0.214*	0.134	0.0722	0.172	0.139	−0.0288	0.0631
	(0.350)	(0.129)	(0.197)	(0.141)	(0.597)	(0.172)	(0.323)	(0.154)
Ag_Edu	−0.570*	−0.173	−0.237	−0.0573	−0.875	−0.256	−0.389	−0.0905
	(0.338)	(0.124)	(0.190)	(0.136)	(0.564)	(0.162)	(0.305)	(0.146)
Yrs_Farm	−0.0323***	−0.00273	−0.0163***	−0.00852*	−0.0481**	−0.00622	−0.0243**	−0.0104**
	(0.0110)	(0.00405)	(0.00620)	(0.00443)	(0.0201)	(0.00580)	(0.0109)	(0.00521)
Income	−0.000484	−0.000753	−0.000320	−0.0000787	−0.000532	−0.000810	−0.000241	−0.000187
	(0.00170)	(0.000622)	(0.000953)	(0.000681)	(0.00282)	(0.000812)	(0.00153)	(0.000729)
% Farm_Inc	2.607***	0.778***	1.194***	0.391	3.799***	1.062***	1.725**	0.598*
	(0.635)	(0.233)	(0.357)	(0.255)	(1.320)	(0.381)	(0.715)	(0.342)
% Gravity [a]	0.278	0.620**	−0.422	0.126	9.450**	2.933**	3.695	1.661
	(0.713)	(0.262)	(0.400)	(0.286)	(4.793)	(1.381)	(2.597)	(1.240)
% Groundwater	1.031*	0.0159	0.633**	0.167	2.352**	0.391	1.225**	0.380
	(0.537)	(0.197)	(0.302)	(0.215)	(0.958)	(0.276)	(0.519)	(0.248)
Shortage_Concern	−0.326	−0.0385	0.0920	−0.348**	−0.715	−0.168	−0.0346	−0.459***
	(0.361)	(0.133)	(0.203)	(0.145)	(0.631)	(0.182)	(0.342)	(0.163)
Temp30	0.0315	−0.145**	0.0372	0.171**	−0.562	−0.291**	−0.244	0.0877
	(0.188)	(0.0688)	(0.105)	(0.0753)	(0.401)	(0.116)	(0.217)	(0.104)
Rainfall30	−0.0903	0.00492	−0.0701	−0.00849	0.159	0.0659	0.0583	0.0158
	(0.108)	(0.0398)	(0.0609)	(0.0435)	(0.191)	(0.0550)	(0.103)	(0.0494)
White River	0.715*	0.413***	0.311	−0.141	1.468*	0.573**	0.801*	−0.173
	(0.421)	(0.154)	(0.236)	(0.169)	(0.789)	(0.227)	(0.427)	(0.204)
Delta	1.162**	0.296	0.618**	−0.178	2.797***	0.711**	1.413***	0.0287
	(0.501)	(0.184)	(0.281)	(0.201)	(0.962)	(0.277)	(0.521)	(0.249)
Constant	−1.531	9.679**	−1.308	−12.26**	27.37	16.62**	12.48	−8.244
	(12.96)	(4.752)	(7.275)	(5.198)	(25.35)	(7.306)	(13.74)	(6.561)
R^2	0.2354	0.2516	0.2089	0.0851				
p-value of Wald test	0.0000***	0.0000***	0.0000***	0.1424	0.0000***	0.0000***	0.0000***	0.0767*

Note. Standard errors reported in parentheses.
[a]In Columns 5–8, instrumental variables (IVs) for these endogenous variables include the following: the number of groups of WMPs used in 2010, peers (family members, friends, or neighbors) used flow meters, average percentage of gravity irrigated acres among other producers, aware of the state tax credits, and percentage of producers in the county that have participated in any federal, state, or local conservation programs in the last 5 years. A Poisson model is first run with the number of WMP groups as the dependent variable. Explanatory variables include IVs and other explanatory variables in Table 8. The predicted values from the Poisson model are then used as IVs in the 3SLS estimation. *Statistical significance at 10%. **Statistical significance at 5%. ***Statistical significance at 1%.

soybean. There is some evidence that using more groups of WMPs negatively correlates with irrigated acres in soybean.

6. Conclusions and Policy Implications

This study describes the WMPs use patterns by producers, identifies the factors related to producers' patterns of WMPs use, and examines the correlations between WMPs uses and irrigated acres. Using the 2016 Arkansas Irrigation Survey, our results show that a majority of the sample producers (about 77%) use two or more groups of WMPs to manage multiple aspects of irrigation. A distinctive pattern of use is observed. Field management practices are the most common among producers that only use one group of WMPs. The combination of field management and water flow practices is the most common among producers that use two groups of WMPs. The combination of field management, water flow control, and water recovery/storage practices is the most common among producers that use three groups.

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Our results show that procedures' decision to use a particular group of WMPs is not made in isolation but rather by looking at all the WMPs available. In the case of Arkansas producers, the use of the field management WMPs and the water flow control WMPs is positively correlated. Which factors are relevant differ by WMP groups. The use of water flow meters, providing producers with education on the looming groundwater shortage problems, awareness of financial assistance available for conservation efforts, such as the state tax credits program, and use of WMPs by family members, friends, and neighbors are associated with increased use of WMPs. However, we find that producers that are older, have smaller farms, and rely more on groundwater are less likely to use some of the WMPs.

Our findings show that different factors are at play for different WMPs. For example, when promoting advanced irrigation scheduling practices, more assistance should be provided to producers with more farming experience. Further research on why the tax credits do not seem to influence the use of targeted practices (field management and tailwater recovery systems and/or on-farm reservoirs) is also important.

Our study also identifies the factors common to multiple groups of WMPs. A producer's decision to use WMPs strongly correlates with the actions of close networks such as family members, friends, and neighbors. Therefore, targeting influential farmers with larger networks may be a good strategy to spread the use of WMPs faster. This is especially important for newer WMPs, such as advanced irrigation scheduling practices, where information sharing is crucial. A novel approach to promote the adoption of WMPs is the 2018 and 2019 Arkansas Irrigation Yield Contest "Most Crop per Drop" (Henry et al., 2019). This is the first such contest in the nation to target producers' Water Use Efficiency (More information about the Arkansas Irrigation Yield Contest and the 2018 report are available online (https://www.uaex.edu/environment-nature/water/contest/)). Contestants have access to soil moisture monitoring equipment, surge valves, and assistance with computerized pipe hole selection and multiple inlet rice irrigation. Water management schools were also held to teach contestants and other producers how to use these WMPs. The contestants can then transfer this new knowledge to other producers.

This study finds a positive correlation between the use of water flow meters and irrigated acres. Although we do not have data to directly assess the effects on total irrigation application or more importantly consumptive water use on farm, it is clear that water used on the additional irrigated acres may fully or partially offset the reduction in irrigation application from using WMPs. Such behavioral responses make sense from the producers' perspective since their objective is to maximize profit. However, it also means that WMPs do not necessarily result in real water savings. Since water meters are being promoted as a valuable water management tool in Arkansas and other states, it is important for policymakers to consider these behavioral responses and take actions to offset the unintended consequences. To achieve the goal of water conservation, the promotion of WMPs should be accompanied by measures to control the total quantity of water allowed for irrigation (Pfeiffer & Lin, 2014). Many tools to mitigate consumptive water use, such as water rights, water pricing, water quota, and direct regulation of crop acreage (or even crop evapotranspiration), already exist. Which measure is feasible, however, depends on the physical, social, economic, and political context. This is an important area for future research.

Our findings echo the importance of a system approach to irrigation management advocated by Sullivan and Delp (2012) and the recommendation of providing tax incentives and credits for integrated irrigation water conservation (Arkansas Natural Resources Commission, 2015). Most sample producers use two or more groups of WMPs to manage multiple aspects of irrigation. The choices regarding different groups of WMPs are also interrelated decisions. Our results show that using more groups of WMPs negatively correlates with irrigated acres in soybean. Most current conservation programs target only one WMP. It is important to design conservation programs that encourage the use of a package of WMPs to manage multiple aspects of irrigation. There is also significant room to spread the system approach. In Arkansas, only about one third of the producers use three out of four groups of WMPs, and only about 8% use all four groups.

There are limitations to our study too. Our data set is cross sectional. The IV estimation suffers from weak instruments. Future research should put more efforts in collecting information on better IVs or panel data so that the impact assessment analysis can be improved. More importantly, follow-up studies should be conducted to analyze why using water flow meters positively correlates with more irrigated acres in Arkansas and why using more groups of WMPs negatively correlates with irrigated acres in soybean. Such research

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will need to be done in collaboration with researchers from outside the field of economics such as agronomy and biological engineering.

Appendix A: Probit Models of Choices Among Groups of WMPs

As a robustness check of the results in Table 5, Appendix A reports estimates of separate probit models of choices among WMP groups. The comparison of results in Table 5 and Appendix A show that most coefficients are close in magnitudes with negligible differences.

Table A1

	Field management	Water flow control	Water recovery/ storage	Advanced irrigation scheduling
Land owner	0.00465	−0.334	0.0313	0.173
	(0.279)	(0.269)	(0.304)	(0.288)
Bachelor or above	0.142	0.199	−0.153	0.210
	(0.249)	(0.220)	(0.244)	(0.227)
Ag_Edu	−0.187	0.302	−0.160	0.304
	(0.258)	(0.210)	(0.217)	(0.246)
Yrs_Farm	0.000572	−0.0101	−0.00535	−0.0220***
	(0.00819)	(0.00716)	(0.00728)	(0.00833)
Income	0.00223	0.000545	−0.000539	0.00316***
	(0.00141)	(0.00102)	(0.00111)	(0.00115)
% Farm_Inc	0.328	0.558	−0.0520	0.0813
	(0.443)	(0.400)	(0.414)	(0.512)
Tir_Acres	0.256***	0.176***	0.0438	0.0144
	(0.0918)	(0.0575)	(0.0563)	(0.0495)
% Gravity	0.731	0.637	0.766	−0.480
	(0.452)	(0.433)	(0.548)	(0.505)
% Groundwater	0.339	0.0302	−1.632***	0.105
	(0.377)	(0.336)	(0.421)	(0.423)
Meter2015	0.176	0.313	0.524**	0.207
	(0.315)	(0.245)	(0.251)	(0.256)
Shortage_Concern	0.731***	0.174	0.0601	−0.102
	(0.247)	(0.231)	(0.248)	(0.268)
Tax_Credit	0.204	0.280	−0.0331	0.744***
	(0.248)	(0.199)	(0.217)	(0.248)
% Cons_Prog	0.979*	−0.0756	0.352	−0.0208
	(0.574)	(0.541)	(0.577)	(0.759)
Peer_Flow/Storage/Field/	0.459	0.508*	1.636***	0.693***
Scheduling	(0.315)	(0.294)	(0.273)	(0.248)
Temp30	−0.264*	−0.117	0.196	−0.0295
	(0.139)	(0.122)	(0.135)	(0.137)
Rainfall30	0.134*	−0.0373	−0.0426	0.128*
	(0.0782)	(0.0630)	(0.0746)	(0.0769)
White River	−0.382	−0.190	−0.282	−0.265
	(0.312)	(0.274)	(0.280)	(0.323)
Delta	−0.415	−0.427	−0.834***	−0.168
	(0.317)	(0.320)	(0.317)	(0.345)
Constant	14.47	8.277	−13.84	−2.325
	(9.670)	(8.430)	(9.203)	(9.301)
p-value of Wald test	0.0088***	0.0001***	0.0000***	0.0040***
Log pseudolikelihood	−75.933	−113.897	−94.598	−76.568

Note. Bootstrapped standard errors are reported in parentheses.
*Statistical significance at 10%. **Statistical significance at 5%. ***Statistical significance at 1%.

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