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# Irrigation efficiency and water withdrawal in US agriculture

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**Abstract**

To meet future food demand and sustainability requirements of society, the agriculture sector faces challenges in both the institutional dimension and the technological dimension. One of the main concerns regarding the current agricultural production pattern is the tremendous amount of water it requires to maintain and boost output. With a changing climate and increasing demand from civil uses, promoting both water allocation efficiency and water application efficiency becomes the focus of policy design. The unintended consequences of water policies, however, have led to extensive debates. This study addresses the key question of whether irrigation efficiency improvement leads to reduced per-area water use. The study assembles a national county-level panel data set on water withdrawal, irrigation technology, and farm operation and demographics. The empirical results show that a higher irrigation efficiency is associated with a lower per-area water application in US crop production. Two alternative efficiency measures are proposed. Depending on how the efficiency is measured, a one standard-deviation efficiency improvement (6–30%) in irrigation can reduce 6–11% of water withdrawal in US crop production. The water saving is about 0.06–0.12 mm/day given a county average irrigation water use of 1.07 mm/day.

*Keywords:* Irrigation efficiency; Public policy; Technology; US agriculture; Water use

## Introduction

By the middle of the 21st century, global population is projected to be 50% larger than the beginning of the century and global grain demand is projected to increase at least by 50% and likely to double (Alexandratos, 1999; Alexandratos & Bruinsma, 2012; Valin *et al.*, 2014). The income effect from economic growth will lead to a significant increase in per capita food consumption in the world, from a current (2005–2007) level around 2,700 Kcal/day to more than 3,000 Kcal/day by 2050 (Alexandratos & Bruinsma, 2012). Given the limited quantity of arable land on Earth and the need to preserve natural ecosystems for a sustainable future, the most feasible solution to accommodate the projected growth is to promote the productivity of the agricultural system. In US agriculture,

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according to the 2007 Census of Agriculture, irrigated farms account for 55% of the total crop sales value on only 57 million acres of land (23 million hectares, 7.5% of the total US farmland). Irrigation can substantially improve land productivity. In general, irrigated land has a higher yield than rainfed ground due to stable soil moisture and longer growing season (Mendelsohn & Dinar, 2003; Khan *et al*., 2006). Therefore, in the coming decades of growing food consumption, irrigated agriculture will play a critical role to meet the demand.

In the USA, irrigation in agriculture accounts for a large proportion of total water withdrawal. In 2010, according to the US Geological Survey (USGS), total irrigation withdrawal accounts for 38% of the total US freshwater withdrawals. In western states, irrigation use makes up as high as 80% of the total withdrawal. Given the increasing population pressure, growing food demand will need more water to expand irrigated agriculture unless there is a significant improvement in water use efficiency (Tilman *et al*., 2002). The current situation of usable water resources, however, is not optimistic. Many irrigated regions in the USA are supplied by groundwater pumped in excess of aquifer recharge. According to Konikow (2013), the rate of groundwater depletion has been consistently increasing since WWII, and the depletion rate has reached almost 25 $km^3$/year in a recent decade (2000–2008). Competition from other civil uses (e.g., growing urban water use, sustainability requirements of natural ecosystems) also reduces water available to agriculture and complicates the situation (MacDonald, 2010).

To increase 'water supply' for irrigation, solutions can be developed from two dimensions: the institutional dimension and the technological dimension. Solutions from the institutional dimension should aim at reshaping water rights and improving allocation efficiency of water resources through, for example, market-based incentives (e.g., Zilberman & Schoengold, 2005; Olmstead, 2010). Solutions from the technological dimension, on the other hand, should focus on promoting water use efficiency (Howell, 2001) and water productivity (van Halsema & Vincent, 2012). Agricultural irrigation efficiency has been relatively low. Postel *et al*. (1996) suggested a global average agricultural irrigation efficiency of 65%. Deng *et al*. (2006) reported an irrigation efficiency only around 40% in the north and northwest of China. Based on estimates by Rost *et al*. (2008), the aggregate irrigation efficiency in the USA is in the range of 60–70%, which is higher than the global average using the same set of estimates. One implication of these findings is that agricultural irrigation efficiency has significant room for improvement. New irrigation technologies such as drip and pivot irrigation systems have been increasingly adopted in US agriculture in recent decades (Stubbs, 2016). While improving irrigation efficiency and boosting productivity, more efficient technologies can also bring environmental benefits such as reducing soil salinization (Tilman *et al*., 2002). The design of water conservation policies needs to consider both dimensions and with caution. Whittlesey & Huffaker (1995) point out that policymakers may overlook the impacts of the technology changes to the hydrologic system and externalities to other water uses. Pfeiffer & Lin (2010) argue that the behavioral response of groundwater users should be considered in conservation policy design and evaluation. Policies have to focus on reducing rates of extraction rather than simply improving irrigation efficiency.

In recent years, incentive-based water conservation programs have become popular in irrigated areas due to their political feasibility (does not change the status quo) and the subsidy for more efficient irrigation systems. From 1997 to 2010, USDA's Environmental Quality Incentives Program (EQIP) provided $4.2 billion in payments to landowners, and nearly a quarter of them were used to support new irrigation systems (Cox, 2013). Theoretical simulation modeling has predicted that irrigation efficiency improvement can lead to global and regional water savings (e.g., Seo *et al*., 2008). The empirical evidence, on the other hand, is mixed and region-specific (e.g., Calzadilla *et al*., 2011; Finger &

Lehmann, 2012). At the intensive margin (how much water is applied per unit of land), irrigation efficiency improvement more likely leads to reduced water use due to the cost effect of efficiency improvement. At the extensive margin (how much land can be irrigated), the relationship is more complicated given the potential irrigation acreage expansion. Pfeiffer & Lin (2014), for example, consider both the intensive margin and the extensive margin and find that there are conditions under which improved irrigation efficiency may increase water usage. Ward & Pulido-Velazquez's (2008) findings suggest that the adoption of more efficient irrigation systems can reduce return flows and limits aquifer recharge. Therefore, policies aimed at reducing water use may, reversely, increase water depletion. Perry *et al*. (2017) present similar evidence. It is worth noting that Perry *et al*.'s (2017) discussion focuses spatially on the Near East and North Africa. The agricultural productivity and institutional settings in these two regions are very different from those of the United States.

The literature has also found different results. Ellis *et al*. (1985), for example, find that using more efficient irrigation systems has little impact on water use, while it does increase the net return of production. Peterson & Ding (2005) show that shifting from flood to drip irrigation systems can reduce both per-area water use and the total groundwater withdrawal. Converting to a center pivot system can increase per-area water use but decrease the total withdrawal. Scheierling *et al*. (2006) find that irrigation technology subsidies can reduce irrigation water withdrawal. According to the *Summary of Estimated Water Use in the United States in 2010*, published by the USGS, the irrigation withdrawal declined 9% as the country shifted to more water-efficient irrigation systems from 2005 to 2010, which continues the trend from 2000 to 2005 (Barber, 2014). There are two fundamental reasons that explain why the impacts of irrigation efficiency improvement are complicated. First, there is likely to be strong disinterest from the status quo distribution of water rights, in which there are not enough incentives to implement the changes unless being properly compensated. In other words, there could be large cross-sectional heterogeneity in the behavioral response to incentive-based water policies. Another reason is the difficulties in water conservation measuring and water resources accounting. Proper water accounting and measuring is the fundamental step for policy design to avoid illusory water conservation (Huffaker, 2008; Karimi *et al*., 2013; Batchelor *et al*., 2017; Food and Agriculture Organization (FAO), 2018). The unintended consequences of promoting irrigation efficiency are often compounded with these institutional constraints and technological barriers.

To enrich the literature and offer an alternative perspective on the debate, this study assembles a national county-level panel data set of water use and irrigation technologies from the USGS to examine the relationship between irrigation efficiency and water withdrawal in US crop production. Due to data limitation, the main focus of the study is on the intensive margin of water use. This paper presents the first study concerning agricultural irrigation efficiency and water withdrawal at the national scale for the USA. The main data are drawn from 2005 and 2010 USGS water use surveys. Socio-economic and farm operation data are matched from the US Census of Agriculture and weather data from the PRISM Climate Group. The socio-economic and farm operation data consist of measures on farm production inputs and outputs, demographics, as well as policies. The empirical results show that, overall, efficiency improvement in irrigation is associated with a reduction of per-area water withdrawal in US crop production. The same relationship holds for all eight states in the US Southwest, even though the Southwest demands substantially more water for irrigating the same unit of land. The results also suggest that surface-water dependency and climatic variability are important drivers of water consumption adjustment in US agriculture.

The remainder of the paper is organized as follows. The section below introduces the empirical methodology and irrigation efficiency measures. Next, is a section describing the data. This is followed by a section that discusses the empirical results and policy implications, and finally, conclusions are drawn.

## Method

### *Regression model*

The relationship between water use and irrigation efficiency is both technological and economic. If there is no economic response and only technological response allowed, irrigation efficiency improvement can lead to water saving directly. In practice, however, profit-maximizing farmers and irrigators are very likely to respond to efficiency improvement by adjusting their production decisions (e.g., irrigating more frequently or more land). Therefore, the simple technological relationship between irrigation water use and system efficiency is often affected by socio-economic factors, location-specific factors, and the policy environment. It is important to control these factors in empirical studies (Mendelsohn & Dinar, 2003). Depending on which margin (intensive or extensive) one is looking at and how strong the economic response can be, the relationship between water use and irrigation efficiency can be positive or negative. This paper examines the relationship empirically at the intensive margin using a fixed-effects regression model:

$$a_{it} = \beta_0 + \beta_1 h_{it} + \beta_2 W_{it} + \beta_3 X_{it} + \eta_i + \tau_t + \varepsilon_{it} \tag{1}$$

where $a_{it}$ is the observed per hectare water withdrawal (a water use measure reported by the USGS[1]) at county $i$ in year $t$. $\beta_0$ is the intercept parameter. $h_{it}$, $W_{it}$, and $X_{it}$ are explanatory variables on irrigation efficiency, weather factors, and farm operation and demographics, respectively. $\beta_1$, $\beta_2$, and $\beta_3$ are the associated parameters to be estimated.$\eta_i$ and $\tau_t$ are county and year fixed effects, respectively. Note that climate factors (which do not vary in a short time period) are absorbed into the fixed effect $\eta_i$. $\varepsilon_{it}$ is assumed to be an *i.i.d* (independent and identically distributed) zero mean error term. The key policy parameter in the model is $\beta_1$, and its sign reveals the relationship between per hectare water withdrawal and irrigation efficiency.

Due to a limited number of years data being available, the model is identified mainly using the cross-sectional variation. The cross-sectional variation can capture the relatively long-run relationship between per-area water use and irrigation efficiency. The model controls for unobserved spatial heterogeneity in irrigation water use through the fixed effects. The fixed effects can also control for variations of water rights regime across regions. Before estimating the model in (1), we first constructed an empirical measure of irrigation efficiency.

### *Irrigation efficiency measure*

In this study, we introduce two alternative but related measures of irrigation efficiency. The first measure is based completely on observational data, which we refer to as the 'direct' measure. The

[1] According to the USGS, water use refers to water that is withdrawn for a specific purpose, such as for public supply, domestic use, or irrigation. See https://water.usgs.gov/watuse/wuglossary.html, accessed October 9, 2017. In this paper, the terms water use and water withdrawal are used interchangeably.

measure is computed as the fraction of cropland irrigated with efficient systems out of the total irrigated acreage, in county $i$ and year $t$. From USGS water use data we know hectares of cropland irrigated with different technologies at the county level. The data report acreage for three irrigation technologies: surface (flood), sprinkler, and micro-system. Among these three, we define sprinkler and micro-system being efficient:

$$h_{it,direct} = \frac{acres\ irrigated_{it}^{efficient}}{total\ acres\ irrigated_{it}} \tag{2}$$

The second measure is constructed as a weighted index integrating observational data and engineering parameters, which we refer to as the 'adjusted' measure. The idea for constructing this irrigation efficiency measure is motivated by the following facts. First, among all farmland that was irrigated in 2010, according to the USGS, 31,600 thousand acres (12,789 thousand hectares, 51%) were with sprinkler systems, 26,200 thousand acres (10,603 thousand hectares, 42%) still with inefficient surface (flood) irrigation, and 4,610 thousand acres (1,866 thousand hectares, 7%) with high efficiency micro-irrigation systems. Another fact is that the application efficiency of each type of irrigation technology has been well documented. Application efficiency is defined as the actual storage of water in the root zone to meet the crop water needs in relation to the irrigation water used (Howell, 2003). For county $i$ in year $t$, the measure is computed as:

$$h_{it,adjusted} = \frac{\sum_{s=1}^{S} H^s\,(acres\ irrigated_{it}^{s})}{total\ acres\ irrigated_{it}} \tag{3}$$

where $H^s$ denotes the standard application efficiency of technology $s$, and $s \in \{1, 2, 3\}$ ($S = 3$ in this study, $H^1 = 90\%$ (micro-system), $H^2 = 75\%$ (sprinkler), $H^3 = 60\%$ (surface and flood), based on Howell (2003)) represent three different technologies reported. Note that, if there is no efficiency variation across technologies, the index reduces to $h_{it,adjusted} = H^s$ for all $s$. Also, $min\{H^s\} \leq h_{it,adjusted} \leq max\{H^s\}$. Here technology-specific irrigated acreage is used as weights.

In general, the adjusted measure can be considered as a refinement of the direct measure. The main disadvantage of the direct index is that it is noisy. First, the difference between sprinkler and micro-system is not considered, both equally efficient. Second, the difference between efficient systems and inefficient systems is binary, not relative. Therefore, this index could be poorly measured. The consequence of this measurement error will be discussed later. A shared concern on both indices is that they cannot capture within technology variation of efficiency due to data limitation. As Koumanov *et al.* (1997) shows, for example, the application efficiency of sprinkler irrigation for almond trees can range from 73% to 79%. In the adjusted index, the pre-assigned values for $H^1$, $H^2$, and $H^3$ can be considered as the average level of efficiency for each technology category, which is consistent with both the real-world practice (e.g., Sonke *et al.*, 2010; Irmak *et al.*, 2011) and the literature (e.g., Koumanov *et al.*, 1997; Howell, 2003). On the other hand, the index, by construction, is resistant to within technology variation as long as there are significant efficiency differences among the three major irrigation technology categories, because it is the relative efficiency differences between categories that matter here. To empirically address the potential attenuation bias due to within technology variation of efficiency, analyses of endogeneity and measurement errors are employed to validate the results.

*Endogeneity*

Endogenous regressors are a common issue with linear regression models, which can lead to biased estimates and hence misleading inference. One reason for irrigation efficiency being endogenous is that water use may reversely affect irrigation efficiency, which violates the independence assumption between error term $\varepsilon$ and efficiency measure $h$. For example, a farmer who incurs a large part of operating expense as irrigation water may find it is profit-improving to switch to a more efficient irrigation system. Another reason for endogeneity is the potential measurement errors associated with efficiency measure $h$, given that the available data does not allow us to examine more detailed categories of irrigation technology.

A common solution to the problem is instrumental variables (IV) estimation. Given that the fixed effects have already absorbed the unobservables that are time-invariant, IV estimation requires instruments that are correlated with efficiency measure $h$ but uncorrelated with the time-varying unobservables determining water use. In this study, we construct a set of instruments for irrigation efficiency using two parts of information: the cross-sectional variation in soil characteristics and the spatial-temporal variation in lagged efficiency measure. The instruments are formed as the interactions between soil characteristics related to irrigation efficiency and a lagged efficiency measure. One motivation for constructing the instruments this way is the strong linkage found between the choice of irrigation technology and soil quality in the literature (Caswell & Zilberman, 1986; Mendelsohn & Dinar, 2003). Stressing soil water management through irrigation technology development also aligns well with the FAO Voluntary Guidelines for Sustainable Soil Management (FAO, 2017). A similar idea of constructing instruments was proposed in Levitt (1997). Three soil characteristics are used: available water capacity (awc), drainage class, and average slope. Their correlations with the choice of irrigation system are straightforward. For regions with large average slope, well drained, and with a soil of low water-holding capacity, it is more likely that irrigators choose efficient irrigation systems over traditional flood irrigation.

A lagged efficiency measure, technically, can be used as an instrument alone. The main concern regarding this instrument is its exogeneity. Apparently, it satisfies the relevance requirement. Irrigation efficiency in 2005 and 2010 are highly correlated as shown in Figure 1 (adjusted) and the supplementary Figure A1 (direct) in the online appendix, which makes it not a weak instrument. However, a lagged efficiency measure may have a strong spurious correlation with the dependent variable. By interacting with the exogenous soil characteristics, we have improved its exogeneity as an instrument. Lagged efficiency measures are constructed by using efficiency measure from 2005 for 2010, and 2000 for 2005. As to be discussed in the data section later, 2000 USGS water use data do not separate crop irrigation from golf irrigation. However, crop irrigation dominates the total irrigation water withdrawal. In 2005, for example, on average more than 95% of the irrigation water is used for crop irrigation across the country. Therefore, the variation of 2000 efficiency measure is mainly driven by variations from crop irrigation.

Another instrument candidate is the cash rent difference between irrigated land and non-irrigated land in the same county. The rationale behind this instrument is that the rent difference should reflect the value of irrigation system attached to the land, and more efficient irrigation systems tend to be more expensive. However, the rent difference may also reflect the degree of abundance in groundwater resource and surface water accessible, which leaves its exogeneity in question. Another problem with using the rent difference as an instrument for irrigation efficiency is that water use may affect rent

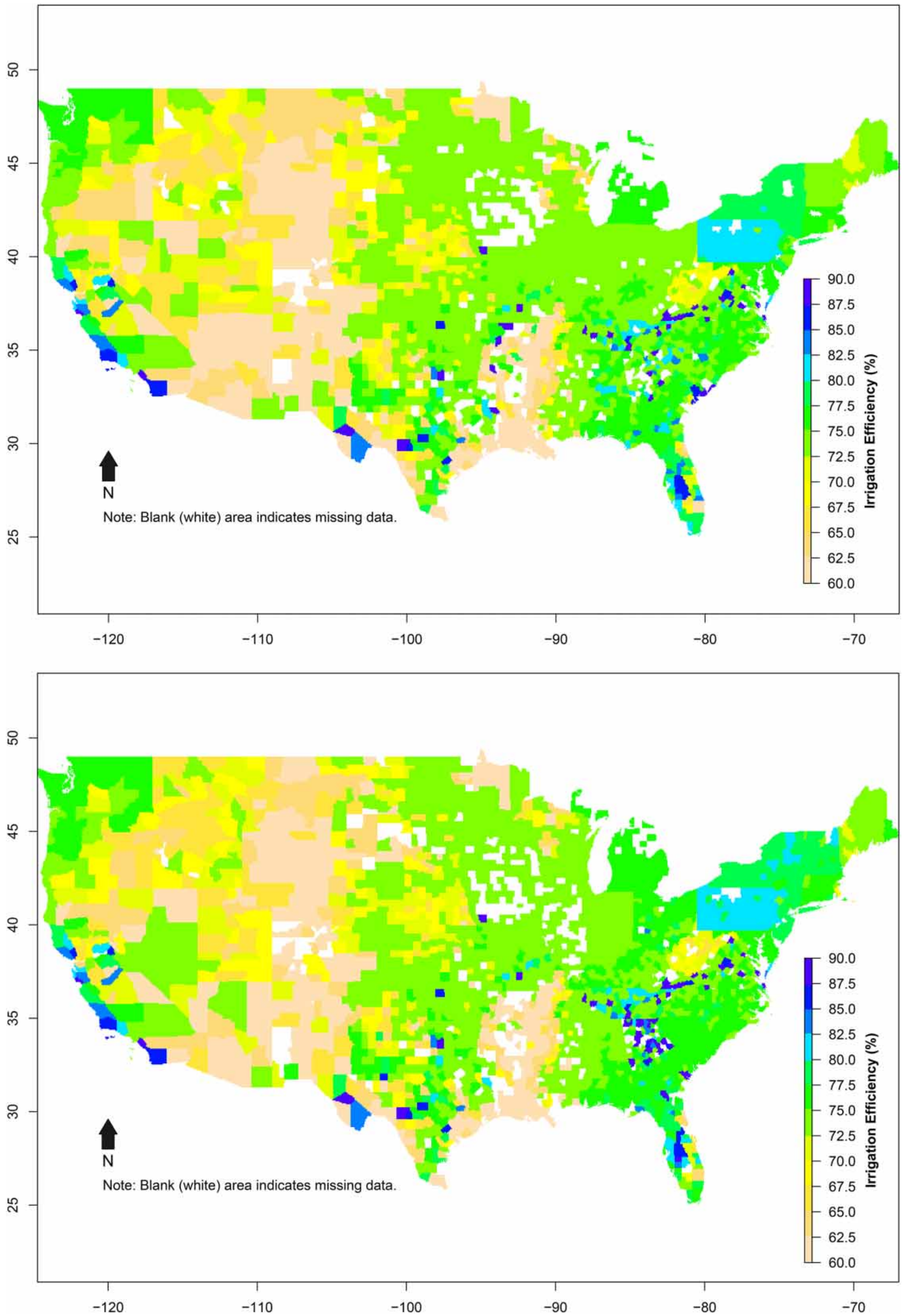


Fig. 1. Irrigation efficiency (adjusted) in US counties, 2005 (top) and 2010 (bottom).

difference, and they both can be confounded by unobserved soil/land quality. A technical limitation with this instrument is that the data on rent difference are only available for about 20% of the counties. Findings with IV estimation are discussed in the Results section.

### *Measurement errors*

Other than the simplification of irrigation technology categories, another potential source of measurement error in the adjusted index is that it uses irrigated acreage by technology (a proxy for irrigation water withdrawal by technology) as weights to construct an efficiency measure. However, the structure of the potential approximation error is unknown and we cannot isolate out a more reliable measure analytically. The same issue applies to the direct index. IV estimation can address the estimation bias due to measurement errors, to some extent. Alternatively, we can explore the sensitivity of parameter estimates to measurement errors by using errors-in-variables models (e.g., see Draper & Smith, 1998). The intuition is that linear regression will lead to a negative bias in the coefficient estimate if the true coefficient is positive and a positive bias if the true coefficient is negative. Defining a reliability measure $r$ as one minus the fraction of noise variance in the total variance of the explanatory variable in question, the idea of the method is to experiment with different degrees of reliability and assess the sensitivity of the interested estimate to possible levels of measurement error. Note that, in general, the reliability measure $r$ must be reasonably larger than the given model's goodness-of-fit statistic $R^2$. This study examines the sensitivity to measurement error on key variable $h$ in different fixed-effects model specifications. Findings are discussed in the Results section.

### *Data*

The data used in this study comes from three main sources. The irrigation water withdrawal and irrigation technology data come from USGS 2005 and 2010 surveys of water use in the USA, which report county-level total withdrawal, sources of withdrawal, and acreage irrigated under different technologies for crop irrigation. The data are used to construct the dependent variable and the irrigation efficiency measure. Note that USGS water use data before 2005 do not separate crop irrigation from other irrigation uses (e.g., golf irrigation). They are excluded to avoid potential bias. The county-level farm operation and demographics data (farm size, annual average conservation payment and total government payment received, farmland value, the principal operator's years of on-farm experience, average farm operating expense, percentage of irrigated farmland, percentage of farms with internet access, and percentage of farms with off-farm water) come from the US Census of Agriculture. However, the census year does not match with the USGS survey year. In this study, the county-level average of 2002 and 2007 census data is used to match USGS 2005 water use data, and the average of 2007 and 2012 census data is used to match USGS 2010 water use data. The same approach has been used in Mendelsohn & Dinar (2003). The soil characteristics data used to construct the instrumental variables are obtained from USGS Water Resources NSDI Node, which is derived from the NRCS State Soil Geographic (STATSGO) Database[2]. The data are then aggregated to the county level. Table A1 in the online appendix reports definitions and summary statistics of the soil variables.

[2] https://water.usgs.gov/GIS/metadata/usgswrd/XML/ussoils.xml, accessed February 1, 2017.

In addition, it is important to account for climatic variability (around current climate normal, not the climate) and water supply in the model. This study includes variables on precipitation level (average monthly precipitation before the growing season and in the growing season) and temperature level (average monthly temperature in the growing season)[3]. Apparently, precipitation and temperature during the growing season affect irrigation water use directly. Precipitation before the growing season can also affect irrigation water use indirectly by changing soil moisture level or influencing ground and surface water recharge. The weather data are obtained from the PRISM Climate Group at Oregon State University. The weather variables are aggregated from PRISM grid level to county level using land area falling into each grid cell as weights. To measure sources of water supply, two county-level variables are constructed. Using the Census of Agriculture data, the percentage of farms with off-farm water supply for irrigation is computed. Another variable is the percentage of surface water in total withdrawals for crop irrigation, which is derived from the USGS water use data. Definitions and summary statistics of variables are summarized in Table 1. Figure 1 shows the spatial distribution of the adjusted efficiency measure in 2005 (top) and 2010 (bottom). Figure A1 in the online appendix shows the same maps for the direct measure.

It is necessary to note that the USGS effectively constructs its county-level water use data making use of a host of primary and secondary data sources. Although the data are created based on rigorous methodology, one can still raise concerns regarding their statistical reliability given that they are not

Table 1. Data summary, variable definition, and descriptive statistics.

| Variable | Definition | Mean | Std. Dev. |
|---|---|---|---|
| $a$ | Per hectare water use per day (mm/day) | 1.07 | 1.17 |
| $h_{direct}$ | Direct irrigation efficiency measure (%) | 82.52 | 30.30 |
| $h_{adjusted}$ | Adjusted irrigation efficiency measure (%) | 73.52 | 5.67 |
| $TPCP_{s1}$ | 1st season precipitation, monthly mean (mm) | 68.33 | 37.77 |
| $TPCP_{gs}$ | Growing season precipitation, monthly mean (mm) | 93.20 | 35.49 |
| $T_{gs}$ | Growing season temperature, monthly mean (°C) | 21.38 | 3.67 |
| *farmsize* | Average farm size (1 K ha) | 0.24 | 0.46 |
| *conservepay* | Annual average conservation payment ($/ha) | 4.10 | 7.96 |
| *govtpay* | Annual average total government payment ($/ha) | 20.41 | 29.06 |
| *landvalue* | Average farmland value ($1 K/ha) | 8.15 | 28.42 |
| *experience* | Average years of principal operator on farm (year) | 21.86 | 2.58 |
| *expense* | Annual average farm operating expense ($1 K/ha) | 1.21 | 7.36 |
| $p-irrigated$ | % of irrigated farmland | 6.78 | 14.31 |
| $p-internet$ | % of farms with internet access | 60.33 | 9.83 |
| $p-offfarm$ | % of farms with off farm water | 7.94 | 12.54 |
| $p-surface$ | *% of surface-water in total withdrawal* | *46.28* | *40.40* |

*Note*: (1) Total number of observations: 5,560; time period of observations: 2005, 2010. (2) 1 Kgal/acre per day equals to 0.9354 mm/day.

[3] Following the convention in the literature, the growing season is defined as April to August. January to March is defined as the period before the growing season.

completely an observational data set. To obtain reliable statistical inference with the data, as discussed in the Method section, this study employs several ways to deal with the consequences of possible measurement errors. Another thing to note on the data is that some of the variables are skewed. In the case of explanatory variables, no assumption on variable distribution is needed to obtain consistent estimates. The dependent variable $a_{it}$ is slightly skewed to the right (positive skewness). The proposed fixed effects model can effectively control for some of the very high levels of water use that cause the skewness so that the residuals from the linear regression model still satisfy the normality assumption reasonably well. This is further discussed in the Results section.

## Results and discussion

### *Empirical results*

The empirical estimation in this study takes advantage of the panel nature of the data to control for unobserved heterogeneity in irrigation water use. Heterogeneity due to the variation of scale is common to spatial data, which is the case in this study, given that county size varies across states. Table 2 (with the direct efficiency measure) and Table 3 (with the adjusted efficiency measure) present the basic panel data model results without any controlling variables on socio-economic factors. The first three columns are random effects specifications. The fourth column and the fifth column are fixed effects specifications, controlling for state fixed effects and county fixed effects, respectively. For comparison purposes, ordinary least squares (OLS) estimation results with pooled data are reported in the online appendix, Table A2. OLS results are qualitatively consistent with panel model results but quantitatively very different. Note that the usual goodness-of-fit measure $R^2$ is not reported here. This is because with maximum likelihood (ML) estimation, the total sum of squares cannot be broken down in the same way

Table 2. Basic panel data model results with the direct efficiency measure.

| | Specification | | | | |
|---|---|---|---|---|---|
| Variable | RE (1) | RE (2) | RE (3) | FE (1) | FE (2) |
| $h_{direct}$ | **− 0.0174***** | **− 0.0156***** | **− 0.0143***** | **− 0.0101***** | **− 0.0085***** |
| | **(0.0009)** | **(0.0009)** | **(0.0009)** | **(0.0009)** | **(0.0008)** |
| $Y_{2010}$ | 0.0177 | 0.0175 | 0.0180 | 0.0187 | 0.0211** |
| | (0.0152) | (0.0151) | (0.0151) | (0.0152) | (0.0104) |
| *southwest* | | 0.6198*** | | | |
| | | (0.0546) | | | |
| *west* | | | 0.7267*** | | |
| | | | (0.0404) | | |
| Fixed effects | – | – | – | State | County |
| Norm of residuals | 75.8074 | 74.0648 | 71.8936 | 54.8470 | 28.3443 |
| *corr* ($a_{it}$, $\hat{a}_{it}$) | 0.5020 | 0.5332 | 0.5703 | 0.7791 | 0.9461 |

*Note*: (1) Asterisks (*, **, ***) indicate statistical significance at 10%, 5%, and 1% confidence levels, respectively. (2) *southwest* = 1 if states are: CA, AZ, UT, CO, NV, NM, OK, TX; *west* = 1 if states are: SD, KS, NM, MT, NE, OK, OR, NV, ID, WA, WY, ND, TX, UT, AZ, CA, CO. (3) In the specification columns, RE and FE represent random effects model and fixed effects model, respectively.

Table 3. Basic panel data model results with the adjusted efficiency measure.

| | Specification | | | | |
|---|---|---|---|---|---|
| Variable | RE (1) | RE (2) | RE (3) | FE (1) | FE (2) |
| $h_{adjusted}$ | **− 0.0725*****<br>**(0.0054)** | **− 0.0639*****<br>**(0.0051)** | **− 0.0550*****<br>**(0.0050)** | **− 0.0350*****<br>**(0.0049)** | **− 0.0221*****<br>**(0.0041)** |
| $Y_{2010}$ | 0.0322**<br>(0.0153) | 0.0303<br>(0.0153) | 0.0294<br>(0.0152) | 0.0266*<br>(0.0153) | 0.0262***<br>(0.0105) |
| *southwest* | | 0.7544***<br>(0.0566) | | | |
| *west* | | | 0.8120***<br>(0.0417) | | |
| Fixed effects | – | – | – | State | County |
| Norm of residuals | 79.4868 | 76.8774 | 74.8552 | 55.9464 | 28.5511 |
| $corr\ (a_{it}, \hat{a}_{it})$ | 0.4242 | 0.4790 | 0.5183 | 0.7688 | 0.9452 |

*Note*: Asterisks (*, **, ***) indicate statistical significance at 10%, 5%, and 1% confidence levels, respectively.

as in an OLS estimation, which makes $R^2$ less useful as a diagnostic tool. Instead, norms of residuals and correlation coefficients between the dependent variable and its predicted values are reported as alternative measures of goodness-of-fit.

The results with the direct efficiency measure (Table 2) and the results with the adjusted efficiency measure (Table 3) are consistent with each other. Their difference in magnitudes can be explained by the way that indices are constructed, which will be further discussed in the full model with other factors controlled. The basic model results convey three observations. First, there exists a statistically significant negative relationship between irrigation efficiency and per-hectare water withdrawal, being consistent with the economic intuition. Second, from 2005 to 2010, there is a slight increase in per-hectare water withdrawal. The trend, however, may be confounded with trends in socio-economic factors. Lastly, the US West and the Southwest use substantially more water for irrigation even in a per-hectare sense. This is consistent with the fact that most of the irrigated agriculture happens in the West. To draw conclusions using the results, other influencing factors have to be taken into account as well. Table 4 reports the full panel data model results with farm operation and demographic factors controlled.

The full model controls for factors from two categories: growing season weather conditions and water supply proxies ($TPCP_{s1}$, $TPCP_{gs}$, $T_{gs}$), farm operation and demographics (*farmsize*, *conservepay*, *govtpay*, *landvalue*, *experience*, *expense*, $p-irrigated$, $p-internet$). The key observation from the basic model still holds. Improved irrigation efficiency in crop production leads to reduced per-hectare water withdrawal. Columns RE (1) and FE (1) correspond to the model with the direct efficiency measure. Columns RE (2) and FE (2) correspond to the model with the adjusted efficiency measure. Based on model fit measures (norm of residuals, $corr\ (a_{it}, \hat{a}_{it})$), the fixed effects specification is preferred here. For the model with the direct efficiency measure, a 10% increase in efficiency is associated with a 0.083 mm water use reduction per day. For the model with the adjusted efficiency measure, a 10% increase in efficiency is associated with a 0.199 mm water use reduction per day. The large difference between two marginal effects can be explained by the difference in constructing the efficiency measures. As shown in Table 1, the direct efficiency measure has a much larger standard deviation. Therefore, a relatively comparable way to look at two estimates is to compute the marginal effects associated with a one standard-deviation change in efficiency. For the model with the direct

Table 4. Full panel data model results.

| Variable | Specification RE (1) | RE (2) | FE (1) | FE (2) |
|---|---|---|---|---|
| $h_{direct}$ | **− 0.0125*** (0.0009)** | | **− 0.0083*** (0.0008)** | |
| $h_{adjusted}$ | | **− 0.0518*** (0.0049)** | | **− 0.0199*** (0.0040)** |
| $Y_{2010}$ | 0.1102*** (0.0236) | 0.1397*** (0.0238) | −0.0527** (0.0241) | −0.0522** (0.0243) |
| $TPCP_{s1}$ | −0.0009*** (0.0004) | −0.0009** (0.0004) | 0.0031*** (0.0004) | 0.0031*** (0.0004) |
| $TPCP_{gs}$ | −0.0043*** (0.0004) | −0.0048*** (0.0004) | −0.0011*** (0.0004) | −0.0012*** (0.0004) |
| $T_{gs}$ | −0.0381*** (0.0057) | −0.0368*** (0.0058) | 0.0899*** (0.0109) | 0.0934*** (0.0110) |
| *farmsize* | 0.5053*** (0.0613) | 0.5645*** (0.0655) | −0.2836** (0.1285) | −0.3057** (0.1294) |
| *conservepay* | 0.0017 (0.0011) | 0.0010 (0.0016) | −0.0006 (0.0013) | −0.0006 (0.0013) |
| *govtpay* | −0.0025*** (0.0009) | −0.0030*** (0.0010) | 0.0002 (0.0007) | 0.0000 (0.0007) |
| *landvalue* | −0.0050 (0.0031) | −0.0054* (0.0032) | −0.0148*** (0.0051) | −0.0148*** (0.0051) |
| *experience* | −0.0922*** (0.0072) | −0.1078*** (0.0075) | −0.0122 (0.0120) | −0.0128 (0.0121) |
| *expense* | 0.0479*** (0.0136) | 0.0520*** (0.0142) | −0.0050 (0.0148) | −0.0020 (0.0149) |
| $p-irrigated$ | 0.0073*** (0.0018) | 0.0100*** (0.0017) | 0.0021 (0.0031) | 0.0022 (0.0031) |
| $p-internet$ | 0.0094*** (0.0021) | 0.0089*** (0.0022) | 0.0039* (0.0022) | 0.0040* (0.0023) |
| Fixed effects | – | – | County | County |
| Norm of residuals | 64.3755 | 65.5220 | 26.3246 | 26.5197 |
| $corr\ (a_{it}, \hat{a}_{it})$ | 0.6594 | 0.6444 | 0.9515 | 0.9508 |

*Note*: Asterisks (*, **, ***) indicate statistical significance at 10%, 5%, and 1% confidence levels, respectively.

efficiency measure, a one standard-deviation increase (30.3%) in efficiency is associated with a 0.2515 mm (or 25.3%) water use reduction per day. Within the 5-month growing season (April–August), that is 38.4795 mm (153 × 0.2515) water use reduction. For the model with the adjusted efficiency measure, a one standard-deviation increase (5.7%) in irrigation efficiency is associated with a 0.1134 mm (or 10.6%) water use reduction per day. Within the 5-month growing season (April–August), that is 17.3502 mm (153 × 0.1134) water use reduction.

Note that the effort and investment necessary to improve irrigation efficiency by one standard deviation could be very different for two measures, which explains the difference in magnitudes of the impacts from a one standard-deviation efficiency improvement. Based on either measure, the saving in water withdrawal is substantial. For the model with the adjusted efficiency measure, another way to interpret the result is to look at efficiency change from one system to another. Shifting from surface irrigation to sprinkler system, or from sprinkler system to micro-system, on average, means a 10~15% increase in efficiency. With a marginal effect of 0.0199 mm/day, a back-of-the-envelope calculation indicates that one-level technology upgrade can be converted, on average, to a 19~28% saving in irrigation water use.

The estimates for other variables are very close between the two models with different efficiency measures. The interpretation here focuses on column FE (2). On average, 2010 irrigation water use decreased by 0.0522 mm (or 4.9%) per day, which is actually consistent with the USGS water use report that the total irrigation water withdrawal has been declining since 2000. Increase of growing season (April–August) precipitation level reduces irrigation water use as expected. A 1-centimeter increase in growing season monthly precipitation results in 0.012 mm/day (or 1.1%) water use reduction. To put this in context, the estimated 0.012 mm/day water use reduction implies a 4.38 mm ($365 \times 0.012$) water use reduction annually. The first season (January–March) precipitation level is a proxy measure of water supply for the following growing season. Higher precipitation (i.e., snow and rain) levels in the first season imply more recharge to both surface water and groundwater. As a supply-side effect, it leads to more irrigation water use. The result shows that a 1-centimeter increase in monthly precipitation in the first season is associated with a 0.031 mm (or 2.9%) irrigation water use increase per day.

Growing season average monthly temperature is an important indicator of plant water stress and growing conditions. Mendelsohn & Dinar (2003), for example, find that high summer temperature is harmful to agriculture. The significant positive estimate of growing season average temperature confirms the detrimental effect. One degree (Celsius) increase in average temperature leads to 0.0934 mm (or 8.7%) additional irrigation water use per day.

Average farm size is expected to be negatively associated with water use in the fixed effects model. Larger farms are more likely to achieve economies of scale in terms of irrigation water use, therefore being economically more efficient. An estimate of −0.3057 suggests that for every 1,000 hectares increase in county average farm size, per hectare irrigation water use is reduced, on average, by 28.6% (0.3057/1.07). Farmland value reflects many drivers, as has been identified in the literature (e.g., Bergstrom & Ready, 2009), which complicates the interpretation of the estimate on *landvalue* variable. In the fixed effects model, for every $1,000 increase in county average farmland value irrigation water use decreases by 0.0148 mm/day (or 1.4%). Overall, the effect is small. There are two potential explanations for the negative relationship found here. First, farmland values tend to be higher in the rainfed East while most of the irrigated agriculture is located in the West and the Mississippi Delta region. Second, it could simply reflect the presence of high-density urban development, which pushes up farmland value through development pressure but reduces both the presence and the economies of scale of irrigated agriculture. The increasing competition between urban civil water use and agricultural water use may complicate the relationship here from another dimension, which can be of interest to future research.

Conservation and total government payments received by farms are used to capture potential impacts from government subsidies (not necessarily to the irrigation system, which is not observed due to data limitation). Both variables have no significant effects. In future research, it is certainly of interest to explore how subsidies directly to irrigation system affect water use. Principal operator's years of experience on the current farm and per-hectare operating expense are used to capture the effects of farm management and input complementarity. Both variables are not significant in the fixed effects model. Percentage of irrigated farmland has a positive but insignificant effect, which may imply that more irrigation-dependent regions use more water at the intensive margin. This is consistent with the fact that more irrigation-dependent regions are less likely to be rainfed. Percentage of farms with internet access is used to capture the impact of technology adoption propensity. It is significant at 10% level with an expected positive sign. However, this variable may be a noisy proxy for the propensity of efficient irrigation technology adoption. Studies have shown that farm internet access decision is strongly associated with household demographics (Mishra & Williams, 2006).

One of the potential concerns about the negative relationship identified between irrigation efficiency and per-hectare water withdrawal in this study is that the relationship may be negative by design. Intuitively, a higher percentage of efficient irrigation, in practice, should lead to lower average water use per hectare. A positive relationship, however, is still possible if the following happens along with the acreage expansion of efficient irrigation, as suggested in a recent FAO discussion paper (Perry *et al.*, 2017): (1) high-value crops replace low-value crops (e.g., switching from hay to pecan in New Mexico); (2) farmers irrigate more frequently. In other words, it is possible to have a positive relationship between irrigation efficiency (as measured by the direct efficiency in this study) and per-hectare water withdrawal if there is strong enough behavioral response (Pfeiffer & Lin, 2014).

### *Source of water*

In many irrigated regions, farmers choose to use a combination of groundwater and surface water given the uncertainty and lack of predictability associated with most of the surface irrigation systems (Siebert *et al.*, 2010). In the context of this study, an interesting question to pursue is whether the source of water matters because water from different sources is usually attached to different institutional settings and costs. To answer the question empirically, two alternative measures ($p - offfarm$ and $p - surface$) for the source of water supply are constructed, as discussed in the data section. Keeping all variables in the fixed-effects specification (FE (1) and FE (2) in Table 4), the model is re-estimated with each source of water measure. Table 5 summarizes the estimation results.

Table 5. Impact of water sources on water use.

| | Specification | | | |
|---|---|---|---|---|
| Variable | FE (1) | FE (2) | FE (3) | FE (4) |
| $h_{adjusted}$ | **− 0.0256***** | | **− 0.0184***** | |
| | **(0.0015)** | | **(0.0045)** | |
| $h_{direct}$ | | **− 0.0049***** | | **− 0.0083***** |
| | | **(0.0002)** | | **(0.0009)** |
| $Y_{2010}$ | −0.0783*** | −0.0802*** | −0.0572** | −0.0564** |
| | (0.0041) | (0.0042) | (0.0251) | (0.0249) |
| $p - offfarm$ | 0.0158*** | 0.0145*** | | |
| | (0.0017) | (0.0017) | | |
| $p - surface$ | | | 0.0021*** | 0.0019*** |
| | | | (0.0005) | (0.0005) |
| Fixed effects | County | County | County | County |
| Number of obs | 1,247 | 1,247 | 5,058 | 5,058 |
| Norm of residuals | 28.9612 | 45.5115 | 26.1827 | 25.9868 |
| $corr\ (a_{it}, \hat{a}_{it})$ | 0.8572 | 0.7046 | 0.9494 | 0.9501 |

*Note:* Coefficient estimates on other variables are suppressed but available upon request.

Coefficient estimates on both measures agree with each other. A higher percentage of farms with off-farm water supply (more likely to be surface water) is associated with more water withdrawal per hectare. Estimates on the percentage of irrigation water withdrawal from surface water confirm the positive relationship. Note that there is a considerable difference in sample sizes when estimating the model with the two different measures, due to limited information on off-farm water supply in the Census of Agriculture data. Most of the available observations on off-farm water supply come from counties in the West. Therefore, it should not affect the qualitative conclusion in any significant way given that it is where most of the irrigated agriculture is located.

### *Endogeneity*

Table A3 in the online appendix reports two-stage least squares (2SLS) estimation results using the instruments for efficiency measure $h$ described in the Method section. Here we focus on the estimations with the interactions between lagged efficiency measure $h_{lag}$ and soil characteristics as instruments. Wu–Hausman $F$ test is used to test if the efficiency measures in question are exogenous. We can not reject the null hypothesis that the variable is exogenous at the 1% confidence level. At the 5% level, we reject the null hypothesis that the direct efficiency measure is exogenous. In this case, IV estimation is preferred. The first stage $F$ test suggests that the proposed instruments for $h_{direct}$ are relevant. Basmann $\chi^2$ test (test of overidentifying restrictions) is used to test if the instruments are valid (checking for exogeneity). The null hypothesis is that the instruments are valid, which we cannot reject at the 5% confidence level.

As noted in Murray (2006), the 2SLS estimation usually produces standard errors larger than those from linear regression. The increase in standard errors can be observed in all four specifications in Table A3. An estimate of −0.0021 implies that a one standard-deviation increase (30.3%) in efficiency leads to a water saving of 0.0636 mm/day (or 5.9%). This suggests that the effect of the direct efficiency measure is largely overestimated in the fixed effects model. Also, the new estimate (0.0636 mm/day) is much closer to the estimate (0.1134 mm/day, or 10.6%) with the adjusted efficiency measure $h_{adjusted}$ which is exogenous as suggested by the Wu–Hausman $F$ test. To sum up, we can conclude that an efficiency improvement of one standard deviation (6–30%) in the irrigation system can save roughly 6–11% of water use in US agriculture depending on how the efficiency is measured, with a combined confidence band between −5 and 15%.

### *Measurement error*

Tables A4 and A5 in the online appendix report the results of errors-in-variables (EIV) estimation with $h_{direct}$ and $h_{adjusted}$, respectively. Comparison between the EIV estimation results and the full fixed effects model results (Table 4) indicates that, if there are classic measurement errors in measuring the irrigation efficiency the fixed-effects model estimates of key parameter $\beta_1$ suffer from an under-estimation bias (positive bias). This suggests that what we have estimated from the fixed effects model is likely a lower bound of the water use impact from efficiency improvement. Of course, the statement only holds if the measurement errors in the variables are only random noise and there is no systematic error. As long as the measurement error is within a reasonable range, inferences based on the fixed effects model and the IV regression results in this study can still be reliable and informative.

### *Policy implication*

Given the importance of adaptation to climate change in agriculture to both food supply and future sustainability, there is a growing interest in understanding adaptation within the agriculture sector. Irrigation has been a major channel for adapting to the changing climate in most of the agricultural regions in the USA, especially the West (MacDonald, 2010; Frisvold & Konyar, 2012; Wang, 2016). In facing declining water resources, many incentive-based water conservation programs have been implemented in recent decades. One of these is to subsidize the installation of more efficient irrigation systems to boost water application efficiency in agricultural production, which has led to extensive debates in both academia and public forum regarding whether irrigation efficiency improvement reduces water use.

The Agricultural Act (Farm Bill) of 2014 has highlighted the regional priorities of conservation policy. Through the Regional Conservation Partnership Program (RCPP), the policy agenda has dramatically shifted the USDA's land and water conservation objective, from a farm-by-farm focus to a regional and watershed level. Under the new policy agenda, stakeholders are encouraged and incentivized to endogenize extensive margin benefits while also accounting for intensive margin benefits. Given such a background, the policy interpretation of the findings in this study needs to be carried out in a broader policy context. Many conservation policies can affect irrigation water use from both the intensive margin and the extensive margin. The same policies may have spillover effects on other sectors of the regional economy. On top of the economic layer of the policy, there are also environmental and ecological values to take into account.

This study could shed some light on at least two water policy issues. One is better water accounting. The USGS has been collecting county-level water use data in the USA since the 1980s. For over three decades, the way that the data are collected has not changed much. This study showcases valuable use of the data. It also suggests that the USGS should consider improving both the structure and the resolution of the data. For instance, the data may be reported/estimated at the hydrologic unit level. Furthermore, advanced water accounting techniques can be readily used now (Batchelor *et al*., 2017; FAO, 2018). The USGS could incorporate these new techniques and improve the information quality of the water use data. For instance, groundwater use and surface water use in irrigation may be reported separately. This will definitely benefit future research that looks at the hydrologic aspect of irrigation. The other one relates to sustainable irrigation water use. This is a multi-dimensional policy issue. It involves policies on water, climate change, land and soil management, ecosystem management, and so on. Through a reduced-form statistical framework, this study demonstrates how soil characteristics may play important roles in calibrating the relationship between efficiency and water use in agriculture.

Admittedly, one limitation of this study is that it does not impart anything regarding the extensive margin of agricultural water use, which is an interesting aspect to pursue as well. In the meantime, this study provides a big picture of the entire agriculture sector regarding its irrigation efficiency and water use. It is the first empirical study at the national scale with publicly available data. Moreover, a complete impact assessment on irrigation efficiency improvement also requires integrating research efforts from all aspects of the agri-environment system (Ward & Michelsen, 2002; Wichelns & Oster, 2006). As mentioned above, the hydrological aspect of the research question is not well explored in this study. That is another fruitful research direction as new data that link groundwater use and surface water use become available.

## Concluding remarks

This study assembles a national county-level data set of water withdrawal and irrigation technologies in US crop production to examine the relationship between irrigation efficiency and agricultural water use. The empirical results show that, overall, efficiency improvement in irrigation is associated with a reduction of per-area water withdrawal in US crop production. The same relationship holds for all eight states in the US Southwest, even though the Southwest demands substantially more water for irrigating the same amount of land. The paper finds that, more precisely, depending on how the efficiency is measured, a one standard-deviation efficiency improvement (6–30%) in irrigation can reduce roughly 6–11% of water withdrawal in crop production. The water saving is about 0.06–0.12 mm/day given a county average water withdrawal at 1.07 mm/day.

The study takes advantage of the panel nature of the data to identify the relationship between irrigation efficiency and agricultural water use at a national scale. The findings do not necessarily contradict those in the literature suggesting the opposite. One reason is that this study focuses on the change in per-area water use (the intensive margin) with possible extensive margin (irrigated acreage expansion) changes implicitly embedded (as a result of the aggregate data), whereas other small-scale studies may be able to explore the extensive margin or both margins explicitly. Also, studies that have found a positive relationship between irrigation efficiency and water use tend to be small scale region-specific analysis. It is likely that the particular economic structure of agricultural production and the unique institutional environment around water rights in those regions catalyze certain observed behavioral response.

Another potential explanation is that irrigation efficiency improvement can lead to spatial re-distribution of irrigation water withdrawals, and the net outcome may turn out to be a reduction (or an increase) in agricultural water use. To test this hypothesis, data collected at a finer spatial scale are needed. The current study can also be further developed in other ways, for instance, assessing the economic impact of efficiency improvement by examining the agricultural output per unit of water (i.e., water productivity, see van Halsema & Vincent (2012)).

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