Climatic Variability and Irrigation: An Analysis of Irrigation Efficiency Patterns in U.S. Counties

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The efficient management of water resources, given rising water demand and projected reductions in precipitation as a direct result of climate change, has become a critical issue. Several regions in the U.S. continue to experience significant drought and water shortages, which directly threatens the viability of agriculture. This has led to an increase in irrigation, which is in direct competition with other uses of water for domestic, industrial, and hydroelectric activities. Consequently, conservation and efficient water use has emerged as an important focal point in water policy related issues in the U.S. (Clemmens et al. 2008; USDA 2014).

The evidence within the United States that establishes the connection between climatic variability and the need for secondary sources of water, such as irrigation, has been building for years. A major argument has been that changing temperature and precipitation patterns will lead directly to modifications in farming systems and resource use (e.g., Mendelsohn, Nordhaus and Shaw 1994; Adams et al. 1995; Mendelsohn and Dinar 2003; Deschenes and Greenstone 2007; Schlenker and Roberts 2009; Hatfield et al. 2014). Most importantly, some of these studies have noted a growing reliance on irrigation (e.g., Mendelsohn and Dinar 2003; Schlenker, Hanneman and Fisher 2005; Deschenes and Greenstone 2007; Hatfield et al. 2014). The implementation of such adaptation strategies can be expected, on the one hand, to reduce the long-run adverse effects stemming from changes in climatic conditions (Schlenker, Hanemann and Fisher 2005), while on the other, putting further pressure on a resource that is becoming increasingly scarce. These developments are clearly not compatible and are likely to increase tensions between farmers and other sectors of the economy (Schaible and Aillery 2012).

According to the U.S. Geological Survey (USGS), the agricultural sector is the second largest consumer of water resources in United States. Combined water withdrawals used in irrigation, livestock and aquaculture accounted for approximately 115,000 million gallons per day, with 62.4 million acres of land under irrigation (USGS 2014). Moreover, U.S. farmers are shifting to higher revenue crops while several climate models predict significant changes in weather, characterized by warmer temperatures and lower precipitation. As a result, it is expected that demand for water will continue to surpass its supply resulting in a strain in water available for household and industrial purposes (Schaible and Aillery 2014). Hence, the threat of water scarcity has become an issue of concern among policy makers and stakeholders alike with conversations on how best to manage this scarce resource being brought to the forefront (e.g., McGuckin, Gollehon, and Ghosh 1992; Weinberg, Kling, and Wilen 1993; Chakraborty, Misra, and Johnson 2002; Wu, Devadoss, and Lu 2003; Lilienfeld and Asmild 2007; Clemmens, Allen, and Burt 2008).

Consequently, in the face of water scarcity, the role of irrigation has become increasingly important in agricultural production. As several regions particularly in the Southwest continue to experience frequent and prolonged droughts, water extraction rates are projected to rise, and with this, concerns with the depletion of ground water sources will escalate. Irrigation systems are likely to be brought under increased scrutiny with a push towards more efficient irrigation methods (e.g., Evans and Sadler 2008; Hatfield et al. 2014; Schaible and Aillery 2014; Zilberman 2014). Hence, understanding the role that improvements in irrigation efficiency can have in alleviating water scarcity is an important area of research and one that can provide useful information to policy makers. We conjecture that farmers adjust their production plans by altering their scale of operations and mix of inputs and outputs based on several factors including differences in soil types and slopes, disparities in temperature and precipitation across regions, water availability, and predominant irrigation technologies. A hypothetical type of adjustment is a shift away from high value crops that require large amounts of water (e.g., almonds, rice, alfalfa) towards crops that are more drought-tolerant and thus require less water. Furthermore, several studies have predicted an increase in irrigated area in response to climatic variability characterized by unpredictable rainfall, rising global temperatures that lead to higher rates of evapotranspiration (e.g. Nelson et al. 2009; Fisher et al. 2007; Padgham 2009).

Sustainable agriculture, characterized as an integrated system of plant and animal production practices that over the long term enhances environmental quality and the natural resource base upon which the agricultural economy depends, requires the protection and enhancement of water resources (USDA 2014). Improved water management practices are required to maximize the economic efficiency of irrigation systems (Schaible and Aillery 2012). Updating and modernizing irrigation technology is one approach that can enhance water-use efficiency generating benefits beyond the farm. Given the sensitivity of agriculture to secondary water sources, this study seeks to analyze irrigation efficiency in the United States. Here we follow Karagiannis et al. (2003) and define irrigation efficiency (IE) as the ratio of the minimum feasible water used to observed water usage associated with a given level of output holding other inputs and technology constant.

The objective of this study is to evaluate irrigation efficiency across U.S. counties and to establish whether IE has improved or deteriorated over time in the presence of climatic variability and diverse environmental and topographic conditions. The results from this study will add to existing knowledge on irrigation efficiency and provide policy makers with insights on how to formulate policies that are compatible with conservation and efficient water use in agriculture. We conjecture that U.S. counties that are heavily reliant on irrigation are likely to exhibit higher IE because water scarcity in these regions would have induced overtime the following adjustments: (i) a shift to less water-intensive crops; (ii) an increase in investments in modern irrigation technology; and/or (iii) the adoption of statutory requirements that regulate the amount of water usage at the farm level. Moreover, irrigation is conducted in geographically diverse regions that face distinct environmental conditions. For example, farming in the western states are heavily reliant on irrigation, whereas in eastern states irrigation practices are mostly supplemental (Wichelns 2010).

Several approaches have been utilized in the literature to evaluate agricultural water productivity and efficiency including: 1) Frontier methods that are commonly used to measure the technical efficiency (TE) component of productivity. These efficiency measures can be divided into: (a) output-oriented TE which is based on the traditional radial measure that incorporates all inputs (e.g., Aigner, Lovell and Schmidt 1977; Meeusen and van den Broeck 1977); and (b) an input-oriented approach which has been used to derive a non-radial measure of efficiency that isolates the TE of a single input, while holding other inputs, output and technology constant (e.g., Kopp 1981; Reinhard, Lovell and Thijssen 1999; Karagiannis et al. 2003); 2) Total factor productivity (TFP) which is defined as aggregate output divided by aggregate inputs used over a given period of time (e.g., O'Donnell 2016) after which a partial factor productivity (PFP) measure can be derived. Such an approach seeks to measures the ratio of aggregate output divided by volumetric measures of irrigation water used, while holding other inputs used in the production process constant (Njuki and Bravo-Ureta 2016); and 3) Single factor productivity defined as output divided by the water input while ignoring other inputs commonly referred to as "crop per drop" (e.g., Seckler, Molden and Sakthivadivel 2003). This approach differs from the partial factor productivity (PFP) approach mentioned in (2) above because PFP accounts for all inputs used in the production process while "crop per drop" ignores all inputs, except water, used in the agricultural production process (e.g., Scheierling et al. 2014).

This article uses frontier methods in order to analyze both irrigation efficiency and technical efficiency. The economic intuition is that a non-radial measure of the irrigation input can be used to quantify the feasible reduction in irrigation water applied. The approach will generate distinct rankings for technical efficiency (TE) and irrigation efficiency (IE) for each Decision Making Unit (DMU) under study.

The Production Technology

The theoretical foundation used here distinguishes between the production technology and the environmental factors that impact the technology. Whereas the production technology is a system, or technique that transforms inputs into outputs, the environmental factors comprise all the exogenous variables that impact the production process but are beyond the control of the firm (O'Donnell 2016). Environmental factors comprise weather variables, and time-invariant physical features such as topography. We refer to all technologies available in period-*t* as the period-*t* metatechnology. The combinations of inputs and outputs that are feasible using a given metatechnology in a given environment is given as:

(1) $T^t(z) = \{ (x, q) \in \Re_+^{M+N} : x \text{ can produce } q \text{ in environment } z \text{ in period } t\}$.

We also assume the following properties regarding the production technologies (see O'Donnell 2016):

P1: $(x, 0) \in T^t(z)$ for all $x \in \Re_+^M$ implying that inactivity is possible;

P2: the output set $P^t(x, z) \equiv \{q : (x, q) \in T^t(z)\}$ is bounded for all $x \in \Re_+^M$;

P3: if $q > 0$, then $(0, q) \notin T^t(z)$, implying that a strictly positive amount of at least one input is required to produce a positive amount of output. This is also referred to as the weak essentiality property;

P4: if $(x, q) \in T^t(z)$ and $0 \leq \lambda \leq 1$, then $(x, \lambda q) \in T^t(z)$, implying outputs are weakly disposable;

P5: if $(x, q) \in T^t(z)$ and $\lambda \geq 1$, then $(\lambda x, q) \in T^t(z)$, implying inputs are weakly disposable as well (this property implies that if an output vector can be generated using a particular input vector, then it can also be produced using a scalar magnification of that input vector);

P6: the output set $P^t(x, z) \equiv \{q: (x, q) \in T^t(z)\}$ is closed, implying the set of outputs that can be produced given an input vector contains all the points on its boundary;

P7: the input set $L^t(q, z) \equiv \{x: (x, q) \in T^t(z)\}$ is closed, implying the set of inputs that can produce a given output vector contains all the points on its boundary.

When these seven properties are satisfied, then the period-*t* metatechnology is said to be regular and it can be represented using a period-and-environment-specific output distance function (ODF), as in (2) below, that is nonnegative, homogeneous of degree one, and non-decreasing in outputs:

(2) $$\ln D_O^t(x, q, z) = inf\left\{\delta > 0: (x, \frac{q}{\delta} \in T^z(z)\right\}.$$

If there are no environmental variables in the production process and there is no technical change, then expression 2 collapses to the distance function of Shephard (1970). In addition, we assume that:

P8: if $(x, q) \in T^t(z)$ and $0 \leq \tilde{q} \leq q$, then, $(x, \tilde{q}) \in T^t(z)$, implying that outputs are strongly disposable. Strong disposability of outputs implies that it is possible to use the same vector of inputs to produce fewer outputs. This guarantees that the output distance function is non-decreasing in outputs;

P9: Conversely, $(x, q) \in T^t(z)$ and $\tilde{x} \geq x$, meaning that $(\tilde{x}, q) \in T^t(z)$, inputs are strongly disposable. Strong disposability of inputs guarantees that it is possible to produce the same outputs using more inputs and that the input distance function is non-decreasing in inputs; and

P10: $(x, q) \in T^t(z)$, and that for all $\lambda > 0$, then $(\lambda x, \lambda^r q) \in T^t(z)$. This last property means that the metatechnology is homogeneous of degree-r. The logarithm of the output distance function is such that $-(1/r)\ \ln D_O^t(x_{it}, q_{it}, z_{it}) = \ln D_I^t(x_{it}, q_{it}, z_{it})$, where r is the degree of homogeneity.

The output distance function that is nonnegative, homogeneous of degree-r, and non-decreasing in outputs can be represented using a Cobb-Douglas (C-D) functional form, which can be expressed as:[1]

(3) $$\ln D_O^t(x, q, z) = \ln q_{it} - \alpha_0 - \alpha_1 t - \sum_{j=1}^{J} \rho_j \ln z_j - \sum_{m=1}^{M} \beta_m \ln x_m.$$

Data and Econometric Specification

The data consist of a panel of county-level input-output data drawn from the U.S. Department of Agriculture, Census of Agriculture for the years 1987, 1992, 1997, 2002, 2007 and 2012. The 'State and County rankings' volume that is published alongside every census report is used to select 340 of the top agricultural counties, based on the market value of agricultural products sold in 2012. The input-output variables utilized include total value of agricultural sales,

[1] If the output distance function (ODF) is represented using a flexible functional form such as the translog specification then the associated metatechnology cannot be regular. This is because the translog ODF is undefined for regions where q=0. As a result the translog ODF does not satisfy properties P1, P3, P6 and P7. Moreover, properties P8 and P9 are only satisfied if all second order coefficients are zero.

agricultural land in acres, livestock (number of dairy cows, beef cows, hogs, sheep, horses, poultry) converted into animal equivalents by taking into account feed requirements for each animal type (USDA 2000), value of machinery and equipment, hired and contract labor, expenditures on intermediate material (fertilizer, chemicals, electricity) and total fuel used in gallons. All monetary values are adjusted to 2016 dollars using the GDP implicit price deflator that is made available by the Bureau of Economic Analysis of the U.S. Department of Commerce.

The input-output data is augmented with contemporaneous monthly averages of temperature and precipitation derived from the Parameter-Elevation Regressions on Independent Slopes Model (PRISM) Climate Group. The PRISM incorporates a climate-mapping system to generate temperature and precipitation information at 4×4 kilometer grid cells for the entire United States and accounts for effects of elevation, coastal proximity, temperature inversions and terrain induced air-mass blockage (Daly et al. 2008, 2012, 2015).

From an agronomic perspective, crop production relies on ambient weather conditions from planting to harvesting so output tends to be influenced not only by average weather but also by weather extremes. The threshold above which temperatures are considered harmful for crop development is considered to be 89.4°F (Ritchie and NeSmith 1991). Consequently, we incorporate in the model the number of days within the growing season (i.e., April 1 to September 30) where temperatures exceeded the crop ambient level. We refer to this non-linear measure as the number of degree-days.

Local precipitation measures are an inaccurate measure of water quantities required for crop growth and animal husbandry. This is because in the absence of adequate rainfall additional water is applied via irrigation. Volumetric measures of agricultural water used at the county-level are obtained from the U.S. Geological Survey and are available for the years 1985, 1990, 1995, 2000, 2005 and 2010.[2] Linear interpolation methods are used to match this data with the input-output data.

Finally, it is important to point out that agricultural production is likely to be impacted by topography and soil characteristics. Therefore, information on land characteristics obtained from the National Resource Inventory of the U.S. Department of Agriculture are incorporated into the model. This information comprises data on soil samples obtained from soil surveys. It contains detailed information on the physical characteristics and soil features such as measures of susceptibility to soil erosion (k-factor), estimates of susceptibility to floods, length of slope, permeability, fraction of land cover under clay and sand, level of moisture capacity, and salinity of the soil. Similar measures of soil characteristics have been used in other studies of climate change such as (e.g., Deschenes and Greenstone 2007; Schlenker, Hanemann and Fisher 2006).

The stochastic production frontier that represents the unknown technology is estimated using a True Random Effects with Random Parameters model (TRE-RP), which is an extension of the true random effects model (see Greene 2005a, b), albeit with one key exception. This exception, as the name of the model suggests, allows for the random variation across DMUs. In this article, in addition to having an intercept that varies across each DMU the parameter for irrigation is also allowed to vary across DMUs. Thus, the TRE-RP can be written as:

$$(4) \quad y_{it} = \alpha_{1i} + \alpha_2 t + \beta_{1i} \ln x_{1it} + \sum_{m=2}^{6} \beta_m \ln x_{mit} + \sum_{j=1}^{13} \rho_j \ln z_{jit} + v_{it} - u_{it}$$

[2] Note that U.S. Geological Survey does not indicate if these volumetric measures are obtained from groundwater or surface water sources.

where y_{it} is the log of output, which can be produced using conventional inputs x_{mit}, irrigation quantity given by x_{1it}, and environmental factors z_{jit}. The parameter α_{1i} is an intercept term, and β_{1i} captures heterogeneity in irrigation water usage across counties. Both are allowed to vary hence inducing variation of the parameters across DMUs (see Greene 2012). The error structure includes the term v_{it}, which captures statistical noise from various sources (e.g., functional form errors) and we assume that $v \sim N(0, \sigma_v^2)$. The term $u_{it} = -\ln D_O^t\,(x_{it}, y_{it}, z_{it})$ is an output-oriented technical efficiency effect with distributional parameters $u \sim N^+(0, \sigma_u^2)$. This output-oriented technical efficiency is a traditional radial measure that incorporates all inputs including irrigation.

Another measure of efficiency that is of interest here is the technical efficiency associated with a single input, in this case irrigation water use. As mentioned above, the economic intuition is that one can obtain a non-radial measure of the irrigation input, while holding output and all other inputs constant. This will enable the evaluation of the extent to which irrigation water applied can be reduced. Based on stochastic frontier models, the input-oriented approach has been previously used to evaluate irrigation water use efficiency by Karagiannis et al. (2003) for a sample of Greek farmers and to measure technical efficiency of an environmentally detrimental input (Reinhard, Lovell and Thijssen 1999). All these papers use a conventional SPF model along with a translog specification.

A key point of departure between these prior studies and this article is our use of a True Random Effects with Random Parameters (TRE-RP) on a Cobb-Douglas framework. As mentioned earlier, a flexible functional form that incorporates squares and cross products of log-inputs and log-outputs violates key properties of a regular metatechnology, notably: inactivity, strong disposability of inputs and strong disposability of inputs, and output and input closedness (see O'Donnell 2012b, 2016). Given that inputs are assumed to be strongly disposable, the distance (resp. production) function is globally nonnegative and nonincreasing (resp. nondecreasing) in inputs. A translog distance (resp. production) function cannot satisfy these properties and its use inevitably leads to a functional form error.

An illustration of irrigation efficiency is provided in Figure 1. The inefficient representative decision-making unit is initially producing output level q_0 using x_1^a units of irrigation water. In Figure 2, OTE is a radial measure where $OTE = 0B/0A$. The minimum feasible quantity of water needed to produce q_0 is denoted by x_1^c; therefore, the maximum possible reduction in irrigation water is given as $x_1^a - x_1^c$; hence, $IE = x_1^c/x_1^a$. The quantity x_1^c is not observed; however, rewriting the latter expression for IE we can get $x_1^c = IE \times x_1^a$. Therefore, the stochastic production frontier in 4 above can be rewritten as:

$$(5) \quad y_{it} = \alpha_{1i} + \alpha_2 t + \beta_{1i} \ln x_{1it}^c + \sum_{m=2}^{7} \beta_m \ln x_{mit} + \sum_{j=1}^{13} \rho_j \ln z_{jit} + v_{it}$$

Note that x_{1it}^c lies on the frontier, a region that is technically efficient, therefore $u_{it} = 0$. The economic intuition is that one can obtain a non-radial measure of irrigation water, holding output and all other inputs constant, and thus establish the extent to which the quantity of irrigation water applied can be reduced. Thus, a measure of irrigation efficiency can be obtained by equating expressions (4) and (5) in order to obtain:

$$(6) \qquad IE_i = (lnx_{1it}^E - lnx_{1it}) = \exp\left(\frac{u_{it}}{\beta_{1i}}\right)$$

Results from equation 6 will enable us to establish how efficient DMUs are at using the minimal possible level of irrigation water. The OTE and IE approach will enable the dual ranking of counties based on both measures.

Results

Before discussing the results, we acknowledge concerns about endogeneity in the stochastic production frontier literature (e.g., Mutter et al. 2013; Tran and Tsionas 2013; Shee and Stefanou 2015). In this article, a likely source of endogeneity is that input choices are likely driven by weather outcomes. For example, extended periods of drought may drive up the demand for irrigation withdrawals. On the other hand, when rainfall is spread evenly throughout the growing season there is unlikely to be need for irrigation. Using intra-annual standard deviation of rainfall from 5 years prior as instruments, a two-stage least squares estimation procedure is conducted to test for endogeneity where the null hypothesis of the Durbin and Wu-Hausman (Hausman 1978) test is that the variable under consideration, in this case irrigation withdrawals, can be treated as exogenous. We obtain an F-statistic=0.56 and a p-value=0.4536 and based on this large p-value we fail to reject the null hypothesis of exogeneity.

Recall that the estimated equation is a True Random Effects with Random Parameters (TRE-RP) model and that we generate distinct partial elasticities of irrigation for each county across each census year. The mean of the random parameter for irrigation as well as for the conventional inputs (i.e., land, labor, capital, livestock, intermediate inputs, fuel) are reported in Table 2. These estimates can be interpreted as partial elasticities. A Wald test for returns to scale where the null hypothesis is constant returns to scale generates an F-Statistic=164.81 and p-value=0.000. Consequently we reject the null hypothesis that this production function exhibits constant returns to scale. Moreover, the sum of the coefficients indicates that the estimated elasticity of scale is 1.15 revealing slightly increasing returns to scale. The ratio of σ_u and σ_v (λ) is equal to 0.917 indicating that the error components (one and two sided) play a similar role in the overall error term.

The estimates of the weather variables reveal that, on average, spring temperatures (April to June), spring precipitation (April to June) and the number of degree-days have statistically significant impacts on the total value of agricultural output. These results indicate that, ceteris paribus, average spring precipitation has a negative effect whereas average spring temperatures have a positive impact on total value of agricultural output. On the other hand, an increase in the number of degree-days (i.e., days with temperatures exceeding 89.4°F) has a negative effect on total value of output.

Finally, results on the impact of land and soil features on total value of agricultural output reveal that regions characterized by clay soils, higher levels of soil permeability, and moisture capacity all result in higher levels of total value of agricultural output. On the other hand, soils characterized as flood-prone, susceptible to soil erosion (k-factor), wetlands, and saline soils contribute, ceteris paribus, lead to lower values of agricultural output.

As mentioned earlier, irrigation efficiency is measured as the minimum feasible quantity of water needed to generate a given level of output at the frontier (Karagiannis et al. 2003). It involves estimating the maximal possible reduction in irrigation withdrawals while holding all other inputs constant. The economic intuition being that the usage of irrigation water input can be progressively scaled back up to a minimal feasible level required for producing a given level of output. Average irrigation efficiency across all counties is estimated to be 79.4% whereas average technical efficiency across all counties is estimated to be 81.4%. An illustration of the kernel densities of irrigation efficiency and technical efficiency is provided in Figure 2. In Table 3, we present results of the best performing Counties based on estimates of irrigation efficiency for the years 1987, 1992, 1997, 2002, 2007 and 2012. Wilchens (2010) conjectures that counties that rely heavily on irrigation for their primary water needs are likely to be more efficient than counties that use irrigation water for supplemental purposes. Based on our results, we find no evidence that this is the case. On the contrary, other than the counties of San Luis Obispo, CA, Santa Barbara, CA, Tillamook, OR and Cavalier, ND, all the other counties that rank highest in terms of irrigation efficiency are located in the eastern half of the United States which is characterized by a farm sector that utilizes irrigation for supplemental needs. In Table 4 we present results of the worst performing counties, again based on our estimates of irrigation efficiency. With the exception of San Bernardino, CA, Comanche, TX and Douglas, NV, the counties that feature on this list are located in the eastern half of the U.S. We also present technical efficiency estimates alongside the irrigation efficiency estimates. We find that counties characterized by high levels of irrigation efficiency are also likely to be highly technically efficient. Conversely, counties that are characterized by low levels of irrigation efficiency are also technically inefficient.

In Table 5 we provide a correlation matrix that illustrates the relationship between irrigation efficiency, technical efficiency, with some of the environmental factors, such as, fraction of clay and sand, susceptibility to soil erosion (k-factor), soil permeability, moisture capacity, spring and summer temperatures, and precipitation. Recall that irrigation efficiency is defined as the minimum feasible quantity of irrigation water needed to produce a given level of output. We find irrigation efficiency to be negatively correlated with sand, and soil permeability, revealing that regions characterized by sandy soils and high levels of soil permeability require higher volumes of irrigation water than the minimum feasible needed to generate a given level of output. In addition, we find irrigation efficiency to be negatively correlated with spring and summer temperatures and precipitation. We surmise that increased levels of spring and summer temperatures lead to higher levels of evapotranspiration necessitating higher volumes of water than the minimum feasible required. On the other hand, irrigation that is conducted in the presence of increased precipitation levels is likely to lead to more than minimum feasible levels required for agricultural output leading to lower levels of irrigation efficiency.

Concluding Remarks

This article uses stochastic production frontier production methods to calculate and evaluate measures of technical efficiency and irrigation efficiency using a sample of 340 counties of the top U.S. agricultural counties based on the total value of agricultural sales. Two distinct approaches are used: an output-oriented technical efficiency approach that radially measures the efficiency of all inputs used in the production process; as well as a non-radial input-oriented approach that isolates and measures the efficiency of a single input. The objective is to evaluate irrigation efficiency across U.S. counties in the presence of climatic variability and diverse environmental and topographic conditions. Our general findings reveal that irrigation contributes positively to output. As regards irrigation efficiency, which we define as the minimum feasible quantity of irrigation water needed to produce a given level of output, we find that irrigation efficiency averaged 79.4%. On the other hand, technical efficiency averaged 81.4% during the period of study, 1987-2012. Our findings also reveal irrigation efficiency to be highly correlated with technical efficiency thus establishing that counties that are technically efficient are also likely to be characterized by high levels of irrigation efficiency. Some studies have observed that states in the western half of the U.S. rely on irrigation for their primary water needs whereas in states located in the eastern half of the country irrigation is mostly supplemental (e.g., Wichelns 2010; Schaible and Aillery 2012). Based on this, we conjecture that counties that are heavily reliant on irrigation water for their primary needs are likely to be more efficient partly because water scarcity has necessitated a move towards less water-intensive crops, investments in irrigation technology, and State and local statutory requirements that regulate the amount of water used. Our results reveal that most of the best performing counties in terms of irrigation efficiency are located in the eastern half of the U.S.

Irrigation efficiency is one dimension that seeks to improve irrigation water management practices across the United States. These results should provide policy makers with insights on how to formulate policies that are compatible with conservation and the promotion of efficient water use under conditions that are characterized by increasing water scarcity.

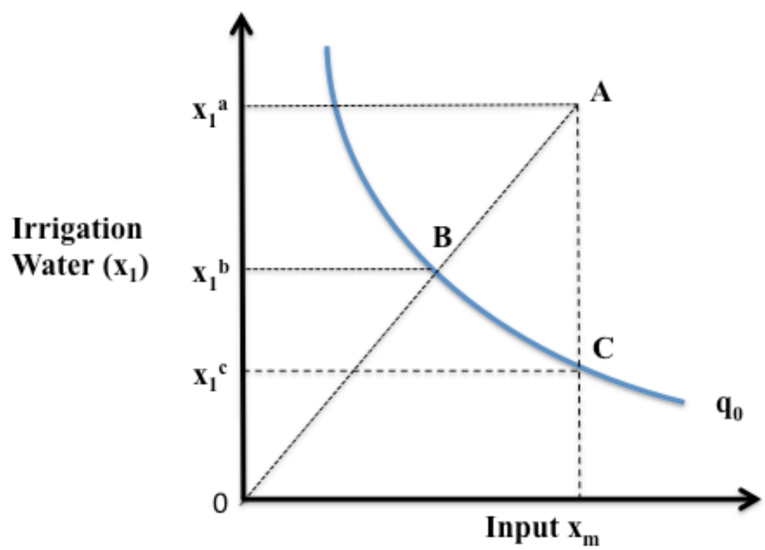

Figure 1: Input oriented irrigation efficiency

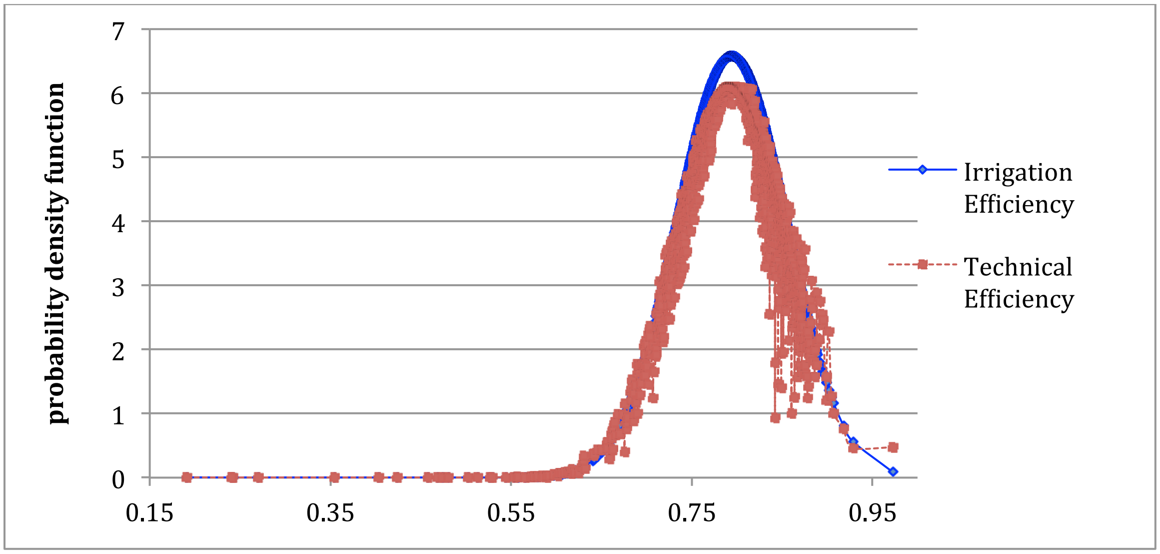

Figure 2: Probability density function for technical and irrigation efficiency

Table 1: Summary Statistics

Variable	Obs.	Mean	Std. Dev	Min	Max
Total Value of Ag. Products ('000 $)	2034	305,463.60	450,905.60	2,405.84	5,157,044.00
Land (acres)	2034	440,795.70	423,976.70	1,047.00	3,112,271.00
Livestock (animal equivalent)	2034	42,334.44	59,285.84	29.69	595,766.50
Machinery ('000 $)	2034	146,154.50	104,642.70	1,223.66	1,030,971.00
Labor (hours)	2034	3,662.06	8,941.37	12.92	96,120.48
Intermediate Inputs ('000 $)	2034	31,287.66	50,825.04	0.00	533,028.40
Fuel (Gallons)	2034	5,503.54	7,054.12	0.00	187,803.70
Irrigation (Mgal/day)	2034	114.65	324.62	0.03	3411.04
Weather Variables					
Temperature (Fahrenheit)	2034	50.92	7.83	31.86	79.25
Precipitation (mm)	2034	71.09	30.54	1.71	231.97
Spring Temperature (Fahrenheit)	2034	59.84	6.44	28.23	81.50
Summer Temperature (Fahrenheit)	2034	69.82	5.89	32.00	91.93
Spring Precipitation (mm)	2034	80.36	35.70	0.00	241.22
Summer Precipitation (mm)	2034	79.52	42.24	0.00	290.91
Degree Days	2034	31.71	34.20	0.00	171.00
Soil Characteristics					
Fraction of Clay	2034	0.17	0.21	0.00	1.00
Fraction of Sand	2034	0.08	0.18	0.00	1.00
Flood Prone	2034	0.12	0.18	0.00	1.00
K-Factor	2034	0.30	0.06	0.02	0.51
Permeability	2034	2.67	2.41	0.25	13.69
Wetlands	2034	0.11	0.11	0.00	0.73
Moisture Capacity	2034	0.18	0.04	0.05	0.30
Salinity	2034	0.01	0.05	0.00	0.64

Table 2: Parameter Estimates of True Random Effects with Random Parameters Model

Variable	Parameter	Coefficient	Std. Error
Land	β_1	0.0317[a]	0.0099
Labor	β_2	0.2920[a]	0.0071
Capital	β_3	0.5719[a]	0.0099
Livestock	β_4	0.1284[a]	0.0059
Intermediate	β_5	0.0847[a]	0.0024
Fuel	β_6	0.0262[a]	0.0039
Spring Temperature	ρ_1	0.9687[a]	0.2648
Summer Temperature	ρ_2	-0.3869	0.3244
Spring Precipitation	ρ_3	-0.0412[a]	0.0054
Summer Precipitation	ρ_4	-0.0020	0.0054
Degree Days	ρ_5	-0.0060[a]	0.0022
Fraction Clay	ρ_6	0.0053[a]	0.0016
Fraction Sand	ρ_7	-0.0009	0.0019
Flood Prone	ρ_8	-0.0052[a]	0.0017
K-Factor	ρ_9	-0.1924[a]	0.0366
Permeability	ρ_{10}	0.0601[a]	0.0226
Wetlands	ρ_{11}	-0.0301[a]	0.0070
Moisture Capacity	ρ_{12}	0.1955[a]	0.0430
Salinity	ρ_{13}	-0.0035[c]	0.0021
Trend	ρ_{14}	0.0204[a]	0.0009
Means for random parameters			
Constant	$\bar{\alpha}_1$	-1.4623[a]	0.5201
Irrigation	$\bar{\theta}_i$	0.0187[a]	0.0047
Lambda	λ	0.9164	0.0718
Sigma (u_{it})	σ_u	0.2399	
Sigma (v_{it})	σ_v	0.2617	

Note: a, b, c denote significance at the 1%, 5%, and 10% levels.

Table 3: Best performing Counties based on Irrigation Efficiency (1987 - 2012)

County	Year	Irrigation Efficiency	Technical Efficiency	Estimated Irrigation Volumes (Mgal/day)
Union, NC	1987	0.878	0.906	3.080
York, ME	1987	0.870	0.892	0.910
Sheboygan, WI	1987	0.869	0.892	1.246
Duplin, NC	1987	0.864	0.894	4.172
Piscataquis, ME	1987	0.864	0.879	0.128
Essex, VT	1992	0.882	0.891	0.090
Union, NC	1992	0.880	0.913	5.380
Frederick, MD	1992	0.876	0.918	8.878
Rockingham, VA	1992	0.875	0.908	6.176
Cavalier, ND	1992	0.874	0.888	0.168
Monroe, WI	1997	0.929	0.963	1.314
San Luis Obispo, CA	1997	0.892	0.897	161.444
Santa Barbara, CA	1997	0.891	0.908	286.252
Mills, IA	1997	0.889	0.909	0.736
Essex, VT	1997	0.889	0.894	0.058
Morris, NJ	2002	0.899	0.922	1.210
Frederick, MD	2002	0.886	0.912	2.382
Tillamook, OR	2002	0.882	0.915	5.194
Rockingham, VA	2002	0.878	0.908	2.672
Cavalier, ND	2002	0.875	0.882	0.028
Jo Daviess, IL	2007	0.918	0.948	1.474
Fayette, KY	2007	0.907	0.938	1.578
Middlesex, MA	2007	0.904	0.930	4.266
Frederick, MD	2007	0.899	0.932	2.342
Cavalier, ND	2007	0.895	0.902	0.066
Wilkin, MN	2012	0.972	0.962	0.170
Cavalier, ND	2012	0.902	0.906	0.056
Traverse, MN	2012	0.895	0.904	0.152
Essex, VT	2012	0.894	0.901	0.122
Union, NC	2012	0.888	0.917	2.966

Table 4: Worst performing Counties based on Irrigation Efficiency (1987 - 2012)

County	Year	Irrigation Efficiency	Technical Efficiency	Estimated Irrigation Volumes (Mgal/day)
Franklin, NY	1987	0.270	0.275	1.378
Berkshire, MA	1987	0.468	0.480	0.876
Grand Isle, VT	1987	0.474	0.491	0.328
Essex, VT	1987	0.544	0.571	0.096
Bennington, VT	1987	0.559	0.585	0.108
Franklin, NY	1992	0.354	0.362	1.704
Lafayette, MO	1992	0.592	0.603	1.790
Chouteau, MT	1992	0.621	0.623	21.856
Loudoun, VA	1992	0.630	0.648	0.682
Portage, WI	1992	0.663	0.665	27.318
Loudoun, VA	1997	0.527	0.545	0.500
Berkshire, MA	1997	0.572	0.586	0.942
Pittsylvania, VA	1997	0.699	0.715	2.020
Comanche, TX	1997	0.711	0.717	37.278
Douglas, NV	1997	0.711	0.715	126.410
Marion, FL	2002	0.247	0.244	18.584
Douglas, NV	2002	0.530	0.522	98.504
San Bernadino, CA	2002	0.565	0.559	187.388
Orange, NY	2002	0.573	0.583	2.140
Windsor, VT	2002	0.580	0.597	0.492
Loudoun, VA	2007	0.424	0.430	2.124
Douglas, NV	2007	0.490	0.485	62.576
Jefferson, WV	2007	0.513	0.535	0.222
Marion, FL	2007	0.554	0.554	15.462
Pittsylvania, VA	2007	0.579	0.588	2.366
Redwood, MN	2012	0.191	0.195	1.480
Robertson, TN	2012	0.242	0.245	2.630
Loudoun, VA	2012	0.404	0.410	2.034
Douglas, NV	2012	0.483	0.470	121.166
Marion, FL	2012	0.505	0.504	25.342

Table 5: Correlation Matrix

	Irrig. Eff.	Tech. Eff.	Clay	Sand	K-Factor	Perme ability	Moisture Cap.	Spring Prec.	Summ. Prec.	Spring Temp.	Summ. Temp.
Irrig. Eff.	1.000										
Tech. Eff.	0.994	1.000									
Irrigation	0.029	0.034									
Clay	0.076	0.067	1.000								
Sand	-0.008	0.001	-0.247	1.000							
K-Factor	0.022	0.022	0.152	-0.620	1.000						
Permeability	-0.027	-0.017	-0.369	0.915	-0.694	1.000					
Moisture Cap.	0.065	0.057	0.186	-0.667	0.361	-0.635	1.000				
Spring Prec.	-0.033	-0.034	-0.151	0.126	-0.265	0.172	0.093	1.000			
Summ. Prec.	-0.014	-0.014	-0.203	0.270	-0.351	0.310	0.006	0.613	1.000		
Spring Temp.	-0.008	0.007	0.180	0.326	-0.089	0.277	-0.360	-0.047	0.024	1.000	
Summ. Temp.	-0.013	0.004	0.153	0.292	-0.043	0.250	-0.362	-0.058	-0.031	0.963	1.000

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