Measuring agricultural water productivity using a partial factor productivity approach

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Abstract

Water and agriculture are inextricably linked. Within Africa, several water-related challenges exist that present numerous obstacles and have the potential to impede Africa's continued economic growth. These include: the threat of climate change, as characterized by extreme weather events such as floods, and frequent and intense droughts; a multiplicity of trans-boundary water resources without a coherent arrangement on riparian rights; lack of sufficient water infrastructure for supply and delivery of the water resource; and lack of official data on water use that can be used to formulate good public policy. All these factors have served to increase water scarcity and to raise the competition for scarce water resources between the agricultural sector and other sectors of the economy, such as industry and urban households. A prerequisite to mitigating these challenges is the establishment of an integrated water management system that promotes water productivity and efficiency. Thus, the primary objective of this study is to highlight methods and techniques for evaluating agricultural water productivity and water use efficiency that are replicable, globally. For this purpose we construct a total factor productivity index using the General index proposed in O'Donnell (2016), thereafter we demonstrate how to decompose the partial productivity of water using U.S. agricultural data for the period 1960-2004.

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Introduction

Water and agriculture are inextricably linked. According to the *United Nations World Water Development Report* (2015), the agricultural sector is the largest consumer of water resources accounting for 70% of all fresh water withdrawals globally. In Africa, the agricultural sector is the single largest economic sector accounting for 32% of total Gross Domestic Product (GDP) and provides direct employment to approximately 65% of the Continent's labor force (World Bank, 2016). Notwithstanding this major contribution, agriculture in Africa faces numerous obstacles including water-related challenges that if not addressed have the potential to adversely affect continued economic growth.

Rain-fed agriculture is the predominant type of production method in Africa, and water scarcity stemming from a changing climate poses a serious threat to this critical economic sector (IPCC 2014). Most importantly, the impact of climate change is especially pronounced given the significant inter-annual and intra-annual variability of temperature and precipitation that has become commonplace in the African Continent (UN, 2016). Climate change has resulted in unprecedented extreme weather characterized by floods, storms, and frequent and intense droughts. Changes in the timing and intensity of rainfall have resulted in decreased availability of water for agricultural purposes and a switch to alternative sources of water (IPCC, 2007; 2014). Smallholder farmers in many parts of sub-Saharan Africa are increasingly turning to irrigation for agricultural production (Giordano et al., 2012). This scenario is further compounded by the fact that farmers face increasing competition for scarce water resources from other sectors of the economy such as industry and urban households (UN, 2015). Beyond extreme weather, climate change has also led to a significant alteration of freshwater and marine ecosystems.

Another important feature is the multiplicity of trans-boundary water resources where a coherent arrangement of riparian rights is lacking and the sharing of said resources can be problematic. Approximately 75% of sub-Saharan Africa falls within 53 international river basin catchments crossed by multiple borders (UN, 2016). Examples of such shared trans-boundary water resources are the Lake Chad basin, the Niger Basin, the Nile basin, the Orange basin and the Zambezi basin. According to the United Nations report (2014), access to water may become the biggest source of conflict and war in Africa over the next 25 years. The report goes on to indicate that such conflicts are likely to be between countries where rivers or lakes are shared by more than one country. The lack of clearly spelt-out riparian rights, and the fact that most water resources in Africa exist as a shared resource across several political boundaries may ultimately prove to be a serious challenge if not addressed.

In addition, most of Africa lacks sufficient water infrastructure that can be used to harness this scarce resource. Currently, only 5% of Africa's potential water resources are developed (Sperling and Bahri, 2014). A lack of water supply and delivery infrastructure means that water is rarely delivered to where it is needed most. Consequently, the full potential of water resources has not been realized.

Moreover, monitoring water use represents a huge challenge considering that official analyses of water-use are non-existent in most African countries. In places where this type of analysis exists, the data system is woefully inadequate. According to the United Nations (2015), reliable data that can be used to evaluate efficiency of water use is often incomplete, unavailable or otherwise inadequate for decision-making purposes (UN, 2015). Yet, data on water-use is indispensable and currently policy makers lack the analysis that is required to implement well-informed public policies.

At first glance, the aforementioned challenges appear to be insurmountable. Notwithstanding, these challenges can be addressed through efficient water management practices. Beginning at the national level, an integrated water resource management approach based on sound systematic knowledge, of both surface and groundwater, is imperative (UN, 2015). In addition, a periodic evaluation of water productivity and water use efficiency is prerequisite in order to promote best practices in the management of water in farming.

Water and economic development are closely interlinked, and poverty oriented water interventions can have meaningful and beneficial direct and long-term social, economic and environmental results (UN, 2016). Raising water productivity and water use efficiency can ensure food security by guaranteeing a steady supply of water, sufficient to meet the demands of the agricultural sector and thus provide sufficient food for a growing population. Increased water productivity can also contribute to poverty reduction as access to water, which is a key input for crop production and animal husbandry, provides incomes, sustenance and livelihoods for rural households.

Water is a common resource not only spatially but also inter-temporally; therefore, the sustainable use of water is also needed in order to guarantee intergenerational equity, thus ensuring that the current benefits of water can be transmitted to future generations (Stiglitz, 2009). In sum, there are several benefits to instituting and promoting water productivity and efficient water use programs.

Water productivity can be defined as "…the ratio of the net benefits from crop, forestry, fishery, livestock and mixed agricultural systems to the amount of water required to produce those benefits" (Molden and Oweis, 2007). An alternative definition is that of water-use efficiency, which is "…the ratio of the minimum feasible water used to observed water usage associated with a given level of output holding other inputs constant" (Karagiannis et al., 2003). According to the USDA (2014), water productivity and efficient water use requires 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 and this requires the protection and enhancement of water resources. Therefore, in a world characterized by growing water scarcity, a primary goal is the efficient use of this vital resource, which requires deriving the most agricultural output using the least amount of water.

Consequently, developing suitable tools and indicators in order to measure water productivity becomes critical to achieving the overall goal of sustainable water resource management. The primary objective of this paper is to highlight methods for evaluating water productivity and water use efficiency, which could be replicated across the globe, provided that adequate data are available. The importance of this is clear, considering that agriculture's share of water withdrawals in Africa accounts for 86% of all freshwater sources compared with 81% in Asia, 71% in Latin America, 39% in North America and 32% in Europe (FAO, 2012). What this means is that, relatively, the agricultural sector in Africa uses the most water, yet generates the least amount of output per unit of water used.

Methodologies

There are several approaches that 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, e.g., water, while holding other inputs, output and technology constant (e.g., Kopp, 1981; 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 total water-usage, while holding other inputs used in the production process constant.

3) Single factor productivity defined as output divided by a single input while ignoring other inputs. Commonly used single factor measure is the "crop per drop" (e.g., Seckler, Molden and Sakthivadivel, 2003). This approach differs from the partial factor productivity (PFP) approach mentioned above because whereas a PFP approach accounts for all inputs used in the production process, the single factor approach focuses on a single input (e.g., water), while ignoring other inputs used in the agricultural production process (e.g., Scheierling et al., 2014).

Partial Productivity of Water (PPW)

A key contribution of this paper is to utilize a measure of partial productivity of water (PPW) within a TFP framework. Accordingly, we define the partial productivity of water as the amount of real output that can be generated using a unit of water, while holding other outputs used in the production process constant. In order to have meaningful partial productivity measures, it is critical that one accounts for all inputs that are relevant in a particular production process. Consequently, our approach combines volumetric quantities of water used in agriculture, weather variables, and input-output data (i.e., yield, land, labor, capital, intermediate materials). The economic intuition behind this approach is that considering the rising water scarcity brought about by climate change, along with the rising demand stemming from increasing population and industrialization, a partial productivity of water measure can provide useful information on how efficient a farm uses a unit of water to produce agricultural output.

Simple partial productivity measures have been widely used in several spheres of economic analysis because they are easy to calculate and to interpret. They have been used to evaluate production technologies across several sectors and across several countries. For example, Owuor (1999), and Nyoro and Jayne (1999) have examined partial productivity measures of land and labor in the agricultural sector in Kenya. The U.S. Bureau of Labor Statistics (BLS) generates regular publications that measure the partial productivity of labor, where a common measure is the real output per labor hour (e.g., Sprague, 2014). Such measures are helpful in formulating public policies aimed at enhancing productivity. Nevertheless, it is important to point out that due to heterogeneity in production technologies across industries and over time, it is necessary to measure the partial productivity of a single input on a case-by-case basis.

As mentioned above, the emphasis of this study is on methods and techniques of evaluating agricultural water productivity with the understanding that such techniques can be replicated elsewhere. In the next section we describe the U.S. agricultural data that is used to demonstrate how to measure partial productivity of water within a total factor productivity (TFP) framework.

Data

The data consist of indices of farm inputs and output across the 48 contiguous states of the U.S. The data was developed by the Economic Research Service (ERS) of the U.S. Department of Agriculture and spans the period 1960-2004.[2] This data is supplemented with information on irrigation withdrawals at the state-level prepared by the U.S. Geological Survey. This data is sourced every fifth year; consequently, linear interpolation is used to obtain the in-between years. In addition to input-output data and irrigation withdrawals, we augment the dataset with state-level monthly average temperature and precipitation information obtained from the National Climatic Data Center (NCDC) of the National Oceanic and Atmospheric Administration (NOAA).

The climatic variables comprise contemporaneous average temperature and precipitation, as well as measures of intra-annual standard deviations of precipitation and temperature. Intra-annual standard deviations capture shocks and volatility within a given year due to unanticipated weather patterns (e.g., Mendelsohn, Nordhaus and Shaw, 2004; Lobell, Schlenker and Costa-Roberts, 2011; Kaminski, Kan and Fleischer, 2012). The maximal possible output in a given year is affected not only by the temperature and precipitation that is experienced in that year, but also by the variation in temperature and precipitation within that year. For example, if all the rain falls on one day, then we expect less output than if it is spread evenly throughout the season. This will help in establishing a clear connection between climatic variability and the need for secondary sources of water.

[2] See Ball et al. 2004 for details concerning the construction of the indices of the input and output data.

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). Consequently, in the face of water scarcity brought about by climate change, irrigation will remain the bedrock of water supply. As several regions particularly in the Southwest continue to experience frequent and prolonged droughts, water extraction rates are projected to increase, 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, the evaluation of partial productivity of water is critical in order to provide market signals as to the value of water, and also to assist in raising water use efficiency. We conjecture that farmers adjust their production plans by altering their scale of operations and mix of inputs and outputs based on several factors, both man-made and natural. Such as differences in soil types and slopes, disparities in temperature and precipitation across regions, differences in outputs, 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 require less water.

The Production Technology

In this section we discuss the methodology that is used to characterize the production technology. Following O'Donnell (2016), we define a period-and-environment-specific technology set that is used to characterize all feasible input-output combinations for a given metatechnology under a set of environmental conditions. The period-t metatechnology in environment z is given as:

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

We assume the following properties: (1) the output set $P^t\,(x, z) \equiv \{q\colon (x, q)\ \in T^t\,(z)\}$ is bounded for all $x \in \Re_+^M$; (2) inactivity is possible, $(x, 0) \in T^t(z)$ for any $x \in \Re_+^M$; (3) 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; (4) 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; (5) 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); (6) 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; and (7) 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 (O'Donnell 2016). If these seven properties are satisfied, then the period-*t* metatechnology can be represented using a period-and-environment-specific output distance function, defined as:

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

The output distance function is nonnegative and homogeneous of degree one in outputs. In addition to the properties listed above, we assume that outputs and inputs are strongly disposable. Strong disposability of outputs implies that it is possible to use the same vector of inputs to produce fewer outputs. Strong disposability of outputs guarantees that the output distance function is non-decreasing in outputs, which means that it can be used to construct output quantity indexes that satisfy the axioms mentioned above. Conversely, strong disposability of inputs indicates that it is possible to produce the same outputs using more inputs. Strong disposability of inputs means that the input distance function is non-decreasing in inputs, which indicates that it can be used to construct input quantity indexes.

We proceed by introducing *i* (state) and *t* (time) subscripts into the notation so that, for example, q_{it} and x_{it} represent the output and input vectors of state *i* in period *t*. The output distance function (ODF) is denoted as:

$$(3) \qquad \ln D_O^t(x_{it}, q_{it}, z_{it}) = \ln q_{it} - \alpha_1 \tau - \sum_{j=1}^{J} \rho_j \ln z_{jit} - \sum_{m=1}^{M} \beta_m \ln x_{mit}.$$

Various functional forms can be used to approximate the unknown output distance function (e.g., Cobb-Douglas, translog, quadratic). We do not appeal to the more flexible and commonly used translog specification because it fails to satisfy the regularity conditions necessary to have a production technology that conforms to economic theory (O'Donnell, 2016) and that satisfies the seven axioms enumerated above. Instead we use a Cobb-Douglas specification form because it satisfies several regularity conditions globally (e.g., O'Donnell, 2016; Guilkey, Lovell and Sickles, 1983). The empirical model that we estimate is written as:

$$(4) \qquad y_{it} = \alpha_0 + \alpha_1 \tau + \sum_{m=1}^{M} \beta_m \ln x_{mit} + \sum_{j=1}^{J} \rho_j \ln z_{jit} + \sum_{k=1}^{K} \gamma_k s_{kit} + v_{it} - u_{it}$$

where: $y_{it} = \ln q_{it}$ is the log of an aggregate output; τ is a time trend; $x_{1it}, \ldots, x_{5it}$ are land, labor, capital, intermediate materials and irrigation inputs; $z_{1it}, \ldots, z_{6it}$ are climatic variables (i.e., contemporaneous temperature and precipitation, as well as intra-annual standard deviations of temperature and precipitation); $s_{1it}, \ldots, s_{48it}$ are state-level fixed effects that capture time-invariant features of the environment; v_{it} is an unobserved variable representing functional form errors (e.g., omitted variables, functional form used to *approximate* the true frontier) and other sources of statistical noise; and $u_{it} = -\ln D_O^t\,(x_{it}, y_{it}, z_{it})$ is a nonnegative technical efficiency effect.

The index that is used to decompose the PPW is a variation of the General TFP index proposed in O'Donnell (2016). It is a proper index in the sense that it satisfies economic-theoretic properties of index theory that include: monotonicity, linear homogeneity, identity, commensurability, proportionality, and transitivity.[3] As indicated above, we define PPW as real output per unit of water used holding all other inputs constant at some predetermined level. If x_1, is the irrigation input, then the logarithm of the partial productivity of irrigation for firm *i* in period *t* is:

(5) $\ln PPW_{it} = \ln q_{it} - \ln x_{1it}$

Thus, given the model in equation 4 we rewrite equation 5 as:

$$(6)\ \ln PPW_{it} = \alpha_0 + \alpha_1\tau + \sum_{m=1}^{M}\beta_m \ln x_{mit} - \ln x_{1it} + \sum_{j=1}^{J}\rho_j \ln z_{jit} + \sum_{k=1}^{K}\gamma_k s_{kit} + v_{it} - u_{it}$$

$$\ln PPW_{it} = \alpha_0 + \alpha_1\tau + \sum_{m=1}^{M}\beta_m \ln(x_{mit}/x_{1it}) + (r-1)\ln x_{1it} + \sum_{j=1}^{J}\rho_j \ln z_{jit}$$

$$+ \sum_{k=1}^{K}\gamma_k s_{kit} + v_{it} - u_{it}$$

The index that compares the PPW of state *i* in period *t* with the PPW of state *k* in period *s* is what we refer to as the partial productivity of water change, which is denoted as:

$$(7)\qquad PPW_{ksit} = \frac{PPW_{it}}{PPW_{ks}}$$

By using the antilogarithm from equation 5 above, the full expression for the change in PPW can be written as:

$$(8)\ \ PPW_{ksit}^{G}$$

$$= \left[e^{\alpha_1(\tau_t - \tau_s)}\right]\left[\prod_{j=1}^{J}\left(\frac{z_{jit}}{z_{jks}}\right)^{\rho_j}\right]\left[e^{(u_{ks}-u_{it})}\right]\left[\prod_{m=1}^{M}\left(\frac{x_{mit}/x_{1it}}{x_{mks}/x_{1ks}}\right)^{\beta_m-\lambda_m}\right]\left[\left(\frac{x_{1it}}{x_{1ks}}\right)^{r-1}\right]\left[e^{(v_{ks}-v_{it})}\right]$$

The first right-hand term in expression (8) is a technology index (TI), the second term is an environment index (EI), the third term is an output-oriented technical efficiency index (OTEI), the fourth term is a measure of input deepening (ID)[4], and the fifth term is an output-oriented scale efficiency index (OSEI). The last term is a statistical noise index (SNI) that accounts for

[3] See O'Donnell (2016) for a discussion on the General TFP index.
[4] See Acemoglu and Guerrieri (2008) for a discussion on the concept of input deepening.

measurement errors, omitted variables and other sources of statistical noise. Thus, expression 6 above says that $PPW = TI \times EI \times ID \times SEI \times OTEI \times SNI$.

Results

Statistical tests and parameter estimates

Maximum likelihood estimators (MLE) are used to estimate the empirical model above. A primary advantage of using MLE methods is that they are asymptotically normal which means that estimators not only converge to the unknown parameters, but they converge at a fast enough rate (Greene, 2012). Prior to discussing the results, we acknowledge concerns regarding the potential for endogeneity in stochastic production frontier models (e.g., Mutter et al., 2013; Tran and Tsionas, 2013; Shee and Stefanou, 2015). In our model, a possible source of endogeneity is that input choices may be driven by weather outcomes. For example, a firm's decision to irrigate is based on the amount of rainfall experienced at a given point in time. Therefore, we conduct a Wu-Hausman test for endogeneity, where the null hypothesis is that the variable under consideration, in our case irrigation, is exogenous. The logarithms of precipitation from 5 years prior are used as instruments. With a Wu-Hausman test statistic = 15.9 and a p-value = 0.00, we reject the null of exogeneity and thus conclude that irrigation is indeed endogenous. Subsequent to a test for endogeneity, we conduct a panel unit root test of Maddala and Wu (1999), and Pesaran (2007). Using 4 lags, the test returns a 5% level of significance for the dependent variable output, and the explanatory variables land, labor, irrigation, precipitation and temperature. In addition, a Pedroni (2004) test indicates that the variables are cointegrated. Verbeek (2008, p. 314) and O'Donnell (2016, p. 336) report that if at least one of the explanatory variables is an I(1) process and the dependent and explanatory variables are cointegrated, even though some of the variables may be endogenous, the slope parameters will remain super-consistent.

A Wald test for the null hypothesis of constant returns to scale generates a test-statistic of 430.6 with a p-value = 0.00. Therefore we reject the null hypothesis that this model exhibits constant returns to scale. Another Wald test to check for the significance of including state-level fixed effects in the model generates an F-stat =97.8 with a p-value=0.00. Hence, we conclude that the state-level fixed effects belong in the model. Finally, we test for the null hypothesis of constant variance (i.e., homoscedasticity) for the statistical errors v. A Breusch-Pagan test generates a chi-square = 0.00 and a p-value = 0.96. Therefore we are confident that heteroscedasticity is not a problem and that the standard errors generated in the estimation process are not be biased.

The parameter estimates for irrigation is 0.0080 indicating that, *ceteris paribus*, irrigation has a positive effect on output. The parameter estimates for the climatic variables reveal that precipitation and the variability of precipitation (i.e., intra-annual precipitation) have statistically significant impacts on agricultural yields, with coefficient estimates equal to 0.0406 and -0.0248, respectively. Extreme climatic events that take place rapidly over a short period of time (e.g., storms and floods) are harder to anticipate and more threatening to agriculture (Lin, Perfecto and Vandermeer, 2008). We conjecture this to be the reason why intra-annual standard deviation of precipitation, which measures within-year climatic shocks, has a negative and statistically significant effect on output. On the other hand, the estimates for temperature and intra-annual standard deviation of temperature reveal that these variables have a negative and a positive effect respectively, albeit statistically insignificant. Adaptive mechanisms already in place, such as drought-resistant crop varieties and on-demand irrigation technologies, are perhaps the reason why temperature and intra-annual standard deviation of temperature have statistically insignificant effects on output.

Decomposition of partial productivity of water

As indicated above, we define partial productivity of water as real output per unit of irrigation water holding other inputs constant. The parameter estimates from equation 4 are used to estimate the PPW, which decomposes into the technological index (TI), the output-oriented technical efficiency index (OTEI), the output-oriented scale efficiency index, the input-deepening index (ID), the climatic effects index (CEI) and the statistical noise index (SNI). The results of the year-to-year change in PPW between 1960 and 2004 are provided in Table 3 below. All indexes in this table compare the relevant variable in a particular year with the value of that variable in Alabama in 1960, which is one. In addition, because the index that we use satisfies the transitivity property, we can make comparisons across different states. The transitivity axiom states that a direct comparison of the TFP of two decision-making units (DMUs) should yield the same estimate of TFP change as an indirect comparison through a third DMU (O'Donnell, 2012). This is also the case for PPW and PPW change.

The interpretation of the estimates in Table 3 is as follows: the first line tells us that the partial productivity of water for Alabama (AL) in 2004 was 23.9% higher compared to Alabama in 1960 (PPW=1.239). In other words, a unit of irrigation water in 2004 generated 23.9% more real output compared to a unit of irrigation water in 1960. In a different entry in Table 3, we observe that a unit of irrigation water in California (CA) in 2004 generated almost twice the amount of real output that a unit of irrigation water generated in Alabama in 2004 ($2.328/1.239 = 1.87$). Across the United States, irrigation water usage appears to have been most efficient in North Dakota (ND) (PPW=3.436). On the other hand, the least efficient usage of irrigation water appears to have been in the Northeast with the states of Connecticut (CT), Massachusetts (MA), Maine (ME), New Hampshire (NH), New Jersey (NJ), Rhode Island (RI) and Vermont (VT) reporting negative partial productivity of irrigation measures. In other words, these states used up more water in 2004 compared to 1960 to generate a unit of real output. Figure 1 presents a complete picture of the partial productivity index of irrigation and its components in the state of California.

Figure 2 below provides an illustration of partial productivity of water in the United States between 1960 and 2004. We observe that Northeastern states were least efficient, in comparison with the rest of the country, in their utilization of irrigation water. On the other hand, the most efficient states at utilizing irrigation water to generate agricultural output were California and New Mexico in the Southwest; Washington, Oregon, Montana and Idaho in the

Northwest; Nebraska, Iowa, South Dakota and North Dakota in the Midwest and Northern plains.

Conclusion

Shifting patterns in temperature and precipitation as well as a general trend towards warming has caused several regions across the globe to face severe water shortages. Within the African continent, the situation is further compounded by a severe shortage of water infrastructure for supply and delivery of the water resource, a lack of official data that can be used to evaluate water productivity, and a multiplicity of trans boundary water resources without a coherent agreement on riparian rights. All these factors have served to increase the level of water scarcity. This has resulted in farm adjustments that rely increasingly on secondary sources of water for their agricultural needs. As farmers continue to put pressure on scarce water resources, irrigation systems are likely to be brought under increased scrutiny with a push towards more efficient methods. Developing tools and indicators necessary for measuring the contribution of the productive and efficient use of water is critical for achieving the overall goal of sustainable water resource management. Consequently, it is important and informative to evaluate the partial productivity of water in a manner that considers all other inputs. In this study we use a Partial Productivity of Water (PPW) approach, which we define as the amount of real output that can be generated using a unit of water, while holding all other inputs fixed. This study demonstrates how to decompose a PPW using a variation of the General TFP index that was first proposed by O'Donnell (2016). The ability to respond appropriately and in a timely fashion to the adverse effects of climate change is expected to have a significant effect on future agricultural productivity and on the efficient use of scarce resources, such as irrigation water.

Figure 1: Partial Productivity of Irrigation Water and its components in California (1960-2004)

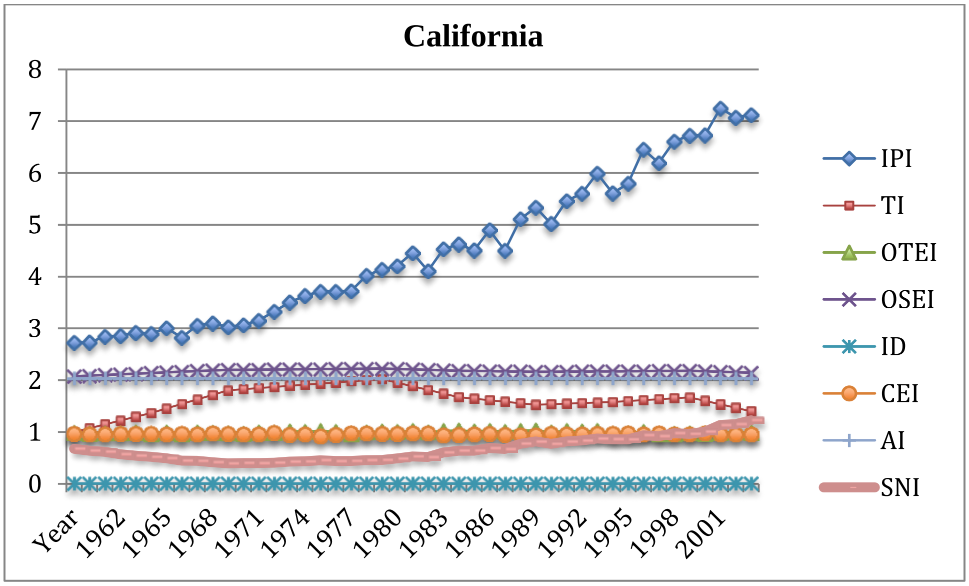

Figure 2: Partial Productivity of Irrigation Water (PPW) Change in the United States (1960-2004)

Table 1: Summary statistics

Variable	Obs	Mean	Std.Dev	Min	Max
Output	2160	1.14	1.16	0.01	9.33
Land	2160	2.10	2.23	0.01	15.12
Labor	2160	2.62	2.31	0.02	12.59
Capital	2160	1.87	1.67	0.02	9.41
Intermediate	2160	0.89	0.82	0.01	4.75
Irrigation ('000 Gallons)	2160	3,034.27	6,019.58	0.03	41,433.34
Temp (Fahrenheit)	2160	52.00	7.63	36.53	72.58
Prec (mm)	2160	76.64	31.67	11.37	170.56
Intra-annual Temp	2160	4.48	2.76	0.99	24.82
Intra-annual Prec	2160	33.27	14.51	4.76	88.02

Table 2: Posterior results

Variables	Coefficient	Parameters	Std. Errors
(Intercept)	α_0	-0.5134	0.3852
Time	α_1	0.0126[a]	0.0004
Land	β_1	0.1407[a]	0.0211
Labor	β_2	0.1211[a]	0.0119
Capital	β_3	0.0032	0.0139
Intermediate	β_4	0.5651[a]	0.0144
Irrigation	β_5	0.0080[a]	0.0033
Precipitation	ρ_1	0.0406[a]	0.0151
Intra-annual Prec	ρ_2	-0.0248[a]	0.0086
Temperature	ρ_3	-0.0012	0.0062
Intra-annual Temp	ρ_4	0.0088	0.0906
AL	γ_1	-0.0864[b]	0.0402
AR	γ_2	0.1279[a]	0.0253
AZ	γ_3	0.6720[c]	0.0478
CA	γ_4	-0.0854[c]	0.0462
CO	γ_5	-0.1688[a]	0.0552
CT	γ_6	-0.1115[c]	0.0576
DE	γ_7	0.4409[a]	0.0279
FL	γ_8	0.2153[a]	0.0201
GA	γ_9	0.0827[c]	0.0446
IA	γ_{10}	0.3583[a]	0.0375
ID	γ_{11}	0.1899[a]	0.0298
IL	γ_{12}	0.4195[a]	0.0419
IN	γ_{13}	0.0824[b]	0.0405
KS	γ_{14}	0.1012[a]	0.0244
KY	γ_{15}	-0.1377[a]	0.0231
LA	γ_{16}	-0.1593[a]	0.0626
MA	γ_{17}	-0.0945[a]	0.0290
MD	γ_{18}	-0.0715	0.0567
ME	γ_{19}	0.0665[c]	0.0393
MI	γ_{20}	0.2340[a]	0.0507
MN	γ_{21}	-0.0112	0.0213
MO	γ_{22}	0.0282	0.0314
MS	γ_{23}	-0.2831[a]	0.0569
MT	γ_{24}	0.1198[a]	0.0457
NC	γ_{25}	-0.5124[a]	0.0533
ND	γ_{26}	-0.4388[a]	0.0717
NE	γ_{27}	-0.0318	0.0349

NH	γ_{28}	-0.4124[a]	0.0458
NJ	γ_{29}	0.1806[a]	0.0368
NM	γ_{30}	0.3686[a]	0.0213
NV	γ_{31}	-0.0178	0.0546
NY	γ_{32}	0.1789[a]	0.0325
OH	γ_{33}	-0.1193[a]	0.0315
OK	γ_{34}	-0.0092	0.0373
OR	γ_{35}	0.1141[a]	0.0320
PA	γ_{36}	-0.3667[a]	0.0957
RI	γ_{37}	-0.0041	0.0220
SC	γ_{38}	-0.0441	0.0458
SD	γ_{39}	-0.0715[a]	0.0220
TN	γ_{40}	0.0387	0.0581
TX	γ_{41}	-0.3256[a]	0.0433
UT	γ_{42}	-0.1722[a]	0.0582
VA	γ_{43}	-0.0069	0.0231
VT	γ_{44}	0.2381[a]	0.0353
WA	γ_{45}	-0.5629[a]	0.0389
WI	γ_{46}	0.2238[a]	0.0443
WV	γ_{47}	-0.6129[a]	0.0563
lambda	λ	1.3100	0.1636
sigma^2	σ^2	0.0097	
$sigma_v^2$	σ_v^2	0.0036	
$sigma_u^2$	σ_u^2	0.0060	
log likelihood		2500.19	

Table 3: Partial Productivity of Water (1960-2004)

State	PPW	TI	OTEI	OSEI	ID	CEI	SNI
AL	1.239	4.683	0.007	0.560	-3.566	-0.002	-2.565
AR	2.563	5.341	0.273	0.504	-3.184	-0.015	-3.053
AZ	1.626	0.143	0.045	0.011	0.133	0.013	1.462
CA	2.328	0.828	0.041	0.077	0.020	-0.015	1.525
CO	1.766	0.720	-0.135	0.069	-0.128	0.013	1.145
CT	-0.202	1.992	0.104	0.750	-4.632	0.021	-2.181
DE	2.003	2.922	0.326	0.653	-4.704	0.011	-1.686
FL	1.854	4.490	0.080	0.373	-1.787	0.004	-1.425
GA	1.681	7.599	0.330	0.717	-5.029	-0.026	-4.755
IA	2.089	-0.240	0.179	-0.146	1.831	0.010	3.163
ID	2.407	1.067	0.098	0.098	-0.071	-0.005	1.377
IL	0.886	10.146	0.321	1.196	-9.410	-0.020	-8.742
IN	1.399	6.362	0.288	0.693	-4.960	0.012	-3.040
KS	1.905	1.229	-0.134	0.112	-0.246	0.046	0.786
KY	1.226	2.569	-0.103	0.489	-2.991	0.036	-1.509
LA	1.965	0.734	0.012	0.050	-0.008	0.014	1.665
MA	-1.021	4.889	-0.026	0.685	-6.127	0.000	-4.619
MD	1.105	2.608	0.168	0.504	-4.357	0.021	-1.907
ME	-0.186	0.713	0.124	0.401	-1.975	0.006	-0.454
MI	0.930	5.548	0.106	0.585	-5.058	-0.003	-4.689
MN	1.145	7.510	0.099	0.809	-6.186	0.013	-6.029
MO	0.611	9.146	0.059	0.892	-7.149	-0.009	-8.176
MS	1.873	2.807	0.024	0.252	-1.628	0.022	-0.571
MT	2.029	1.438	0.286	0.138	-1.062	0.043	-0.169
NC	1.522	5.394	-0.088	0.543	-3.817	-0.017	-3.640
ND	3.436	1.474	0.636	0.133	-0.754	0.025	0.882
NE	2.202	3.244	0.019	0.308	-1.860	0.022	-1.173
NH	-0.363	0.388	0.121	0.282	-3.128	-0.009	-1.040
NJ	-0.306	2.282	-0.040	0.249	-2.947	0.038	-1.859
NM	2.410	1.038	0.096	0.098	0.171	0.010	1.255
NV	1.909	-0.021	0.018	-0.016	0.960	0.018	2.252
NY	0.205	1.378	-0.151	0.126	-1.596	0.033	-0.633
OH	1.135	3.410	0.074	0.365	-2.381	0.056	-1.797
OK	1.264	1.914	-0.257	0.160	-0.307	0.016	0.187
OR	2.230	0.443	0.272	0.042	-0.373	-0.018	1.526
PA	0.992	4.148	0.092	0.496	-0.283	0.035	1.494
RI	-0.871	0.507	0.174	0.726	-7.122	0.035	-2.200
SC	1.406	2.801	-0.022	0.240	-1.237	-0.017	-0.018

SD	2.013	1.790	0.102	0.165	-1.003	0.005	0.136
TN	0.720	2.802	-0.312	0.351	-1.574	0.032	-1.322
TX	1.875	-0.162	-0.101	-0.024	1.003	0.004	2.294
UT	1.478	0.428	-0.017	0.042	-0.144	0.014	1.055
VA	1.234	0.716	-0.134	0.046	-0.078	0.010	0.858
VT	-0.035	0.428	-0.040	0.358	-2.183	0.033	-0.669
WA	2.588	0.008	0.225	-0.016	0.821	-0.032	2.831
WI	0.117	7.027	-0.205	0.708	-6.084	-0.011	-6.576
WV	1.417	0.136	-0.032	-0.859	9.930	0.012	2.324
WY	1.058	0.688	-0.297	0.060	0.079	0.016	0.821

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