Output-oriented and environmental efficiency scores in the High Plains Aquifer

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Abstract

This paper aims to calculate the output-oriented and irrigation-oriented efficiency scores in counties over the High Plains Aquifer (HPA) region. The main hypothesis of the paper is that the output-oriented scores will be overall greater than the irrigation-oriented efficiency scores (or environmental efficiency scores), as producers are more concerned about production than about water use. The data is from 1960 to 2018, and it includes 204 counties. The output is the county's aggregated agricultural production. The inputs are fertilizers and chemicals indexes, as well as share of irrigated land. The inefficiency term is a function of climate variables, such as precipitation, degree-days, and extreme rainy days. Panel Stochastic Frontier Approach (PSFA) was used to calculate the elasticities of the inputs, as well as the marginal effects of the climate variables on the inefficiency term. The results showed that, overall, the output-oriented score was 0.87, meaning that counties produced 13% less than the efficient level. The overall environmental efficiency score was 0.20. After perform a t-test, it was concluded that the mean of the output-oriented score was greater than the mean of the environmental efficiency score, which was the hypothesis of the paper. Finally, precipitation appears to have more effect on the inefficiency than warm days (degree-days above 33 Celsius degrees). For future papers, we aim to analyze the effect of climate change on counties' agricultural production, and consequently, revenue.

1. INTRODUCTION

In the last decades, there has been a growing concern about the depletion rate of the High Plains Aquifer, and some experts advocate that this phenomenon can have a significant impact on the ecosystem, food production, and species that live in the region (Rosegrant and Cline 2003; Scanlon et al. 2012). According to a report from McGuire (2017) – USGS, there was a decline in the water level the HPA of 15.8 feet from predevelopment years to 2015, and 0.6 feet from 2013 to 2015.

The irrigation plays an important and profitable role in the High Plains Aquifer Area. The HPA provides 30% of the U.S. irrigated groundwater (Steward et al. 2013). In addition, according to Garcia, Fulginiti, and Perrin (2019), the marginal productivity of irrigation across the High Plains Aquifer was worth approximately $3.5 billion in 2007. Therefore, farmers are willing to irrigate their planted areas in order to increase their production, and it can lead to a greater depletion rate of the water storage of the aquifer.

Thus, it is important to address how efficiently the farmers are using irrigated land from the HPA, and how efficiently they are producing. In order to provide answers to these concerns, the main objectives of this paper are to measure the output-oriented and irrigated-land-oriented efficiency scores in the counties over the High Plains (Ogallala) Aquifer.

The hypothesis is that, overall, the efficiency scores in the irrigation-oriented setting will be lower than the ones measured in the output-oriented setting, given that farmers are revenue-maximizers rather than irrigation-minimizers. In addition to that, there is no cost for using the water from the aquifer other than operational costs (e.g., pumping).

In addition to that, climate change can affect technical efficiency in the farms, and consequently agricultural production. Chen, Dennis, and Featherstone (2021) analyzed the effect of weather variables on technical efficiency of 540 Kansas wheat farms from 2007/08 to 2016/17. In order to estimate that, they used a panel stochastic frontier approach (PSFA). They found that extreme temperature is negatively related to technical efficiency. Moreover, they found a nonlinear relationship between precipitation and technical efficiency. Finally, they concluded that an increase in precipitation variability caused by climate change could significantly impact farms in Kansas.

Based on that, this paper also aims to analyze the impact of weather variables on the technical efficiency scores in the counties over the HPA region. In order to do that, I will follow the methodology used by Chen, Dennis, and Featherstone (2021), and apply it for the whole HPA region.

Lilienfield and Asmild (2007) measured the water use efficiency in the Western Kansas portion of the Ogalalla aquifer from 1992 to 1999. Using a DEA approach, they found that, on average, farms were using a water excess of 692m^3/ha, representing almost half of the water used. However, differently from the present paper, these authors did not intend to compare the water-oriented efficiency scores to the output-oriented scores. In addition, they focused only in a small portion of the aquifer, while the present paper analyzes the whole region, and they use of water instead of irrigated land.

2. THEORETICAL APPROACH

This paper uses a production function to build the stochastic frontier model. Different types of technology can be imposed in the production function. The Cobb-Douglas technology was chosen because it imposes that the production function is monotonic and concave with respect to inputs. The Cobb-Douglas production function can be defined as follows:

$$y = f(x,z) = e^{-\mu(z)} \prod_{j=i}^{J} x_j^{\beta_j} \tag{1}$$

where x_j's refer to the traditional inputs, β_j's are the parameters of each input, $\mu(z)$ is a term of inefficiency related to exogenous variables z. I adapted this model to include variables that are not traditional inputs, but affect the production function. Then:

$$y = f(x,z) = e^{-\mu(z)+\sum_{l=1}^{L} \beta_l x_l} \prod_{j=i}^{J} x_j^{\beta_j} \tag{2}$$

where x_l's refer to variables that can shift the production, and β_l's are the parameters related to these variables. Following Chen, Dennis and Featherstone (2021), we define the term of inefficiency as:

$$\mu(z) = \exp(\sum \psi_m z_m) \tag{3}$$

where ψ_i are parameters to be estimated.

By taking the logarithm of Equation (2), and plugging (3):

$$\log y = \sum \log(x_j)\, \beta_j + \sum x_l \beta_l - \exp(\sum \psi_m z_m) \tag{4}$$

a. Output-oriented analysis

Technical efficiency can be calculated by using either an output-oriented model, or an input-oriented model, or a model that is oriented for both inputs and outputs. In the output-oriented model, the idea is to maximize the level of outputs, given the level of inputs. In this sense, the Panel Stochastic Frontier Approach (PSFA) can be used to estimate Equation (4):

$$\log y_{it} = \alpha_i + \sum \log x_{it}^{j} \beta_j + x_{it}^{l} \beta_l + \lambda T - \mu(z)_{it} + v_{it} \tag{5}$$

In this paper, i indexes counties and t indexes year. y is agricultural production per acre of land; the traditional inputs (j) are fertilizer and chemicals; the variable that shift the production function (l) is share of irrigated land; and z are climate variables. The term α_i refer to fixed characteristics of cross-sectional units (in this paper, cross-sectional units are counties), and term λT is a linear time trend parameter. μ is positive and it is the indicator of technical inefficiency, and v_{it} is an error term with normal distribution, mean zero and variance σ_v^2. To find the value of the output-oriented technical inefficiency for each county i in each year t, we need to take the exponential of $-\mu_{it}$:

$$\theta_{it} = \exp(-\mu_{it}) \tag{6}$$

The technical inefficiency θ_{it} varies from zero to one: $0 \leq \theta_{it} \leq 1$. County i in year t is considered efficient if $\theta_{it} = 1$. Consequently, any county i in year t that presents a technical efficiency value less than one is considered inefficient. θ_{it} can be interpreted as the ratio between observed quantity of output and the efficient level of output. Therefore, if θ_{it} is equal to 0.8, that means that county i in year t is producing 80% of the efficient level of output y – or, similarly, county i in year t is producing 20% less output than the efficient level.

In Figure 1, DMU A is considered inefficient, whereas DMUs B and C are efficient. Note that A uses the same amount of inputs as B, but it produces fewer outputs. In Figure 1, the level of output-oriented efficiency of A is given by $\theta^A = \frac{y^A}{y^B} = \frac{4}{12} = 0.33$. Then, the amount that DMU

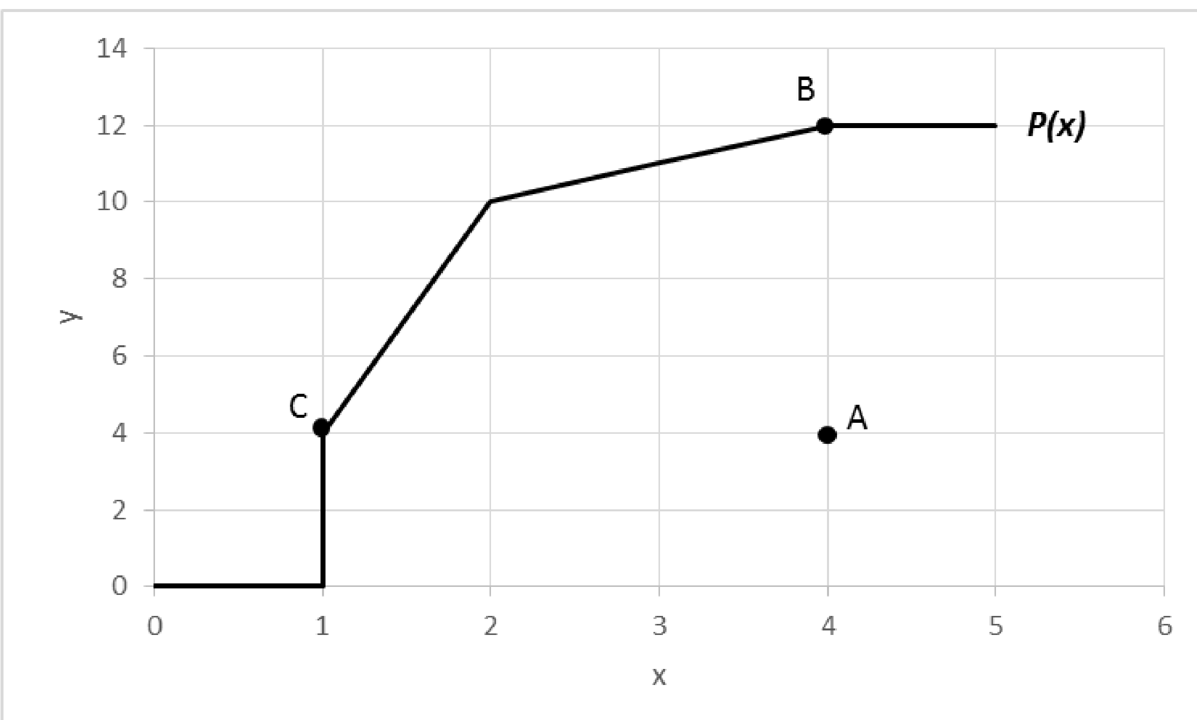
A should be producing is given by $y^{A*} = \frac{y^A}{\theta^A} = \frac{4}{0.33} = 12$. Therefore, in order to be output-oriented efficient, DMU A should have produced three times the amount observed.

Regarding the interpretation of the parameters related to inputs in Equation (5), β_j refers to the elasticity of production with respect to input j, and β_l is the semi-elasticity of production with respect to share of irrigated land.

We are also interested on the effect of climate variables on technical efficiency. Chen, Dennis and Featherstone (2021) showed that the elasticity of technical efficiency with respect to climate variables is given by:

$$\frac{\partial log\theta_{it}}{\partial log Z_{it}^m} = -\mu_{it} Z_{it}^m \psi_m \quad (7)$$

Figure 1 – Illustration of efficient and inefficient DMUs



b. Irrigation-oriented analysis

For the input-oriented setting, the idea is to minimize the level of inputs, given the level of output. Therefore, the level of inputs vary in order to reach a point in the efficient frontier. In Figure 1, this means that the DMU A should use the same level of input as the DMU C, as they both produce the same amount of output.

The input-oriented score assumes that all inputs should be minimized. However, in this paper, we are concerned with the irrigation share only. From now on, I will be referring to the irrigation-oriented model as the environmental model. The irrigation-oriented score is given by the ratio of the efficient use of share of land irrigated over the observed value. Then:

$$EE = \frac{x_l^F}{x_l} \tag{8}$$

where EE refers to the irrigation-oriented efficiency score and x_l^F is the efficient level of irrigation share. EE ranges from zero to one, and units with EE=1 are considered efficient. To calculate the irrigation-oriented score, there is no need to run another econometric model. This is because when a county is output-oriented efficient, it must be irrigation-oriented efficient as well (Kumbhakar, Wang, and Horncastle, 2015). Following (Reinhard, Knox Lovell, and Thijssen, 1999), we can find the irrigation-oriented efficiency score using Equation (5). When the county is efficient, the term μ_{it} in Equation (5) is equal to zero. Therefore, we can rewrite the model as:

$$\log y_{it} = \alpha_i + \sum \log X_{it}^j \beta_j + x_{it}^l \beta_l + \lambda T + v_{it} \tag{9}$$

Then, by taking the difference between (5) and (9), it can be seen that:

$$\beta_l \left(x_{it}^l - x_{it}^{lF} \right) - \mu_{it} = 0 \tag{10}$$

$$x_{it}^l - x_{it}^{lF} = \frac{\mu_{it}}{\beta_l} => x_{it}^{lF} = x_{it}^l - \frac{\mu_{it}}{\beta_l} \tag{11}$$

$$EE_{it} = \frac{x_{l,it}^{lF}}{x_{it}^{l}} = 1 - \frac{\mu_{it}}{x_l \beta_l} \quad (12)$$

If a unit is output-oriented efficient, $\mu_{it} = 0 \Rightarrow EE_{it} = 1$, proving that output-oriented efficient counties must be irrigation-oriented efficient as well.

Note that calculating EE_{it} only makes sense if $\beta_l > 0$. Otherwise, the input is either neutral or bad for production, and EE_{it} is not useful. In addition, it is only possible to calculate the environmental efficiency for counties that have nonzero values for the share of irrigated land. Therefore, if a given county has zero irrigation share in a given year, it will not be possible to calculate its environmental efficiency for that specific year, even though it is still possible to calculate the output-oriented efficiency score for this observation.

A possible problem that may arise from Equation (12) is the existence of negative scores for environmental efficiency. A negative score means that a given county in a given year should "produce" irrigation, instead of using it. It does not have any logical sense. Hence, in this paper, we replaced negative environmental efficiency scores by zero. That is, these DMUs should reduce irrigation to zero in order to be environmental efficient.

Going back to Figure 1, note that the input-oriented score of DMU A is given by $\mu^A = \frac{x^C}{x^A} = \frac{1}{4} = 0.25$. Therefore, the DMU A must have used one-quarter of the amount of inputs that it actually used. By multiplying the observed level of input by the input-oriented efficiency score, we find the quantity of inputs that DMU A must use to be efficient: $x^{A*} = x^A * \mu^A = 4 * 0.25 = 1$.

3. DATA AND ESTIMATION

a. Data

The dataset is an unbalanced panel data consisting of county-level data for 204 counties over the HPA for the period of 1960-2018. The dataset contains 11,629 observations.

Crop production and land data were extracted from the agricultural surveys conducted by the National Agricultural Statistics Service of the U.S. Department of Agriculture (NASS, USDA) and from the Agricultural Census (both available online – QUICKSTATS). Fertilizers and chemicals data were extracted from the Agricultural Census. Climate data are from Trindade (2011). Capital and Labor were not included as inputs because they are not separated between crop and livestock production. That is, there is no information of the sector that capital and labor are employed in, and it could bias the estimators of other inputs.

In this paper, the output is the agricultural production. First, we multiplied each commodity produced by each county and each year by its dry matter. Then, we transformed all commodities production into tons, and we aggregated them by county and year.

Fertilizer and chemicals are index quantities based on information about expenditures and prices of these inputs. Adams, NE-1960 is the base county and year. Irrigated land is the ratio of the irrigated land over the total planted area. In some cases, both irrigated harvested area and irrigated planted area where reported. In these situations, it was used the one with the largest area.

Climate variables are degree-days, precipitation, and extreme rainy days. The degree-days variables refer to the total of days in a year with reported temperature above a given temperature. In this paper, it is used five classification of degree-days: from -5 to 8 Celsius degrees; from 8 to

15 Celsius degrees; from 15 to 33 Celsius degrees, and above 33 Celsius degrees. Precipitation is the annual cumulated precipitation, in centimeters. Extreme rainy days is built based on Schär et al. (2016) and Myhre et al. (2019). First, for each county, it was calculated a threshold of extreme rain equal to the 99th percentile of precipitation in the period between 1960 and 1990. Then, it was constructed a dummy that assumed value 1 if the total amount of precipitation for a given day was greater than the threshold. Then, the variable "extreme rainy days" refer to the number of days in a year in which the threshold was trespassed. Table 1 shows the descriptive statistics of the variables used in the model.

Table 1 – Descriptive Statistics

Variable	Unit	Mean	Std. Dev.	Min	Max
Production (y)	Tons	1.39	0.95	0.04	42.49
Fertilizer	Index	2.08	1.81	0.00	11.07
Chemical	Index	5.60	6.33	0.01	41.52
Irrigation	%	22.12	22.07	0.00	100.00
Precipitation	Inches	15.40	4.94	0.66	55.40
Extreme rainy days	Days	1.92	1.45	0.00	11.00
DD: -05 ~ 08C	Degree-days	36.68	10.17	0.00	77.12
DD: 08 ~ 15C	Degree-days	39.95	7.04	0.00	73.48
DD: 15 ~ 33	Degree-days	103.00	14.57	0.00	146.01
DD: > 33	Degree-days	3.06	2.44	0.00	27.75

The average production in the sample was 1.39 tons. The maximum level of production in the sample was close to 42.5 tons.

The mean of share of irrigated land is 22.12%, with minimum of 0%. Since this variable was not included in the Cobb-Douglas production function as a traditional input, the observations with zero share of irrigated land will not have production equal to zero – that explains why the minimum value observed for production is greater than zero. However, as already mentioned, it will not be possible to calculate the environmental efficiency scores for observations with zero irrigation (Equation 12).

Minimum of precipitation was 15.40 inches per year. Overall, degree-days between 15C and 33C were the most common in the sample period – 103 per year, overall. On the other hand, degree-days above 33C were the least common: around 3 days per year. Extreme rainy days had a mean of around 2 days, and a maximum of 11 days. The maximum was observed once in the sample, and it happened in Donley County, Texas, in 2015.

b. Estimation

As in Wang and Ho (2010), the term μ_{it} in Equation 5 is defined as:

$$\mu_{it} = h(z_{it}) \cdot u_i^*, \text{ where } u_i^* \sim N^+(\mu, \sigma_u^2) \quad (13)$$

where $\sigma_u^2 = \exp(C_u)$. h(.) is a positive function (in this paper, in an exponential form) of a 1x6 vector of climate variables –already presented in Table 1. u_i^* follows a half-normal distribution, and it exhibit a scaling property (Alvarez et al., 2006). u_i^* is unique to each county, and does not change over time.

Equations (5) and (13) are jointly estimated using the same approach as in Wang and Ho (2010). The model is estimated using Maximum Likelihood. After the estimation, μ_{it} is calculated for each county and year. Then, the technical inefficiency scores in the output-oriented model (θ_{it}) is calculated as in Equation (6).

I programmed this model on Stata using the command *sf_fixeff* available in the package *sfbook* proposed by Kumbhakar, Wang and Horncastle (2015).

4. PRELIMINARY RESULTS

a. Skewness Test

Before running the PSFA model, Kumbhakar, Wang and Horncastle (2015) propose a skewness test to check the presence of inefficiency. According to the authors, it is only justified to apply the PSFA method if there is a negative skewness in the distribution of the error term when the inefficiency term is not inserted in the regression.

Then, Equation (5) is run without the inefficiency term μ_{it}. Consequently, the climate variables is not inserted in the regression, as it is included in the inefficiency term. After the estimation, the error term v_{it} is stored, and its skewness is analyzed. Table 2 shows the summary of v_{it}.

Table 2 – Summary of v_{it}

Mean	4.36E-10
Std. Dev.	0.9136849
Variance	0.8348201
Skewness	-1.781128
Kurtosis	7.414046

The Skewness of v_{it} is negative and has a value of -1.78, which is an evidence of the existence of an inefficiency term. In order to check if the statistic is significant, Stata's *sktest* is run, and the values are presented in Table 3. The null hypothesis of the test is no skewness.

Table 3 – Skewness/Kurtosis tests of v_{it}

Skewness/Kurtosis tests for Normality				
				joint
Variable	**Pr(Skewness)**	**Pr(Kurtosis)**	**chi2(2)**	**Prob.>chi2**
v_it	0.000	0.000	290.04	0.000

The p-value related to skewness (first column) is very small – indistinguishable from zero. Therefore, the null hypothesis of no skewness is rejected. Thus, the error has a left-skewed distribution, and the skewness is statistically significant. According to Kumbhakar, Wang, and Horncastle (2015), this means that there is no need to revisit the specification of the model at this stage, and we can proceed to estimate the frontier model.

b. Panel Stochastic Frontier Approach

Equations (5) and (13) are estimated and results are presented in Table 4. As explained before, except for the share of irrigated land parameter, the parameters of 'frontier' variables represent the elasticity of production with respect to the inputs. The parameter related to the share of irrigated land represents semi-elasticity.

Table 4 – Panel Stochastic Frontier Approach estimates

log production	Coeff.	Std. Err.	z	P>z	[95% Conf. Interval]	
Frontier						
log fertilizer	0.1022	0.0076	13.3700	0.0000	0.0872	0.1172
log chemical	0.1731	0.0051	33.8500	0.0000	0.1631	0.1831
irrigation share	0.2996	0.0243	12.3300	0.0000	0.2520	0.3472
efficiency variables						
precipitation	-0.0904	0.0106	-8.5000	0.0000	-0.1112	-0.0695
extreme rainy days	-0.0207	0.0016	-1.2500	0.2100	-0.0053	0.0012
DD: -05 ~ 08C	-0.0276	0.0039	-6.9900	0.0000	-0.0353	-0.0199
DD: 08 ~ 15C	-0.0315	0.0049	-6.3700	0.0000	-0.0411	-0.0218
DD: 15 ~ 33	-0.0001	0.0030	-0.0300	0.9780	-0.0060	0.0058
DD: > 33	0.0508	0.0072	7.1000	0.0000	0.0368	0.0649
Vsigmas						
_cons	-2.2548	0.0133	-169.2200	0.0000	-2.2809	-2.2287
Usigmas						
_cons	3.3895	1.0402	3.2600	0.0010	1.3507	5.4283

Fertilizer, chemicals and irrigation share appear to affect the production in our model. A 1% increase in fertilizers increase the production by 0.1%, whereas it increases by 0.17% when chemicals increase by 1%. Since the coefficient related to the irrigation share refers to the semi-elasticity, a raise of 1 percentage point in the share of irrigated land increases agricultural production by 0.3%.

The interpretation of the estimates of the climate variables is not straightforward. Climate variables are directly related to the inefficiency term. A piece of useful information that we can extract from Table 2 is that negative coefficients related to these variables mean that they reduce inefficiency, whereas positive values mean that the variables increase inefficiency. Therefore, we found that only degree-days above 33 Celsius degrees increase inefficiency. Precipitation, degree-days between -5 and 8 Celsius degrees, and degree-days between 8 and 15 Celsius degrees decrease inefficiency. Extreme rainy days and degree-days between 15 and 33 Celsius degrees do not appear to affect the inefficiency term.

By using Equation 7, we can calculate the elasticity of technical efficiency with respect to climate variables. Since extreme rainy days and degree-days between 15 and 33C were not statistically significant, we will not calculate their elasticities. Table 5 summarizes the elasticities.

Table 5 – Elasticities of climate variables on output-oriented score

Variable	Mean	Std. Dev.	Min	Max
Precipitation	0.1745	0.1615	0.66	2.1298
DD: -05 ~ 08C	0.1325	0.1256	0.00	1.9273
DD: 08 ~ 15C	0.1745	0.1921	0	3.1217
DD: > 33	-0.0319	0.0785	-2.2482	0

Precipitation and degree-days between 8 and 15C present the greatest elasticities. In fact, they have the same mean value: 0.1745. That means that if either precipitation or degree-days between 8 and 15C increases by 1%, the output-oriented efficiency score will increase by 0.17%. The lowest elasticity is related to degree-days above 33 Celsius degrees. If these increase by 1%, output-oriented efficiency score will decrease by 0.03%.

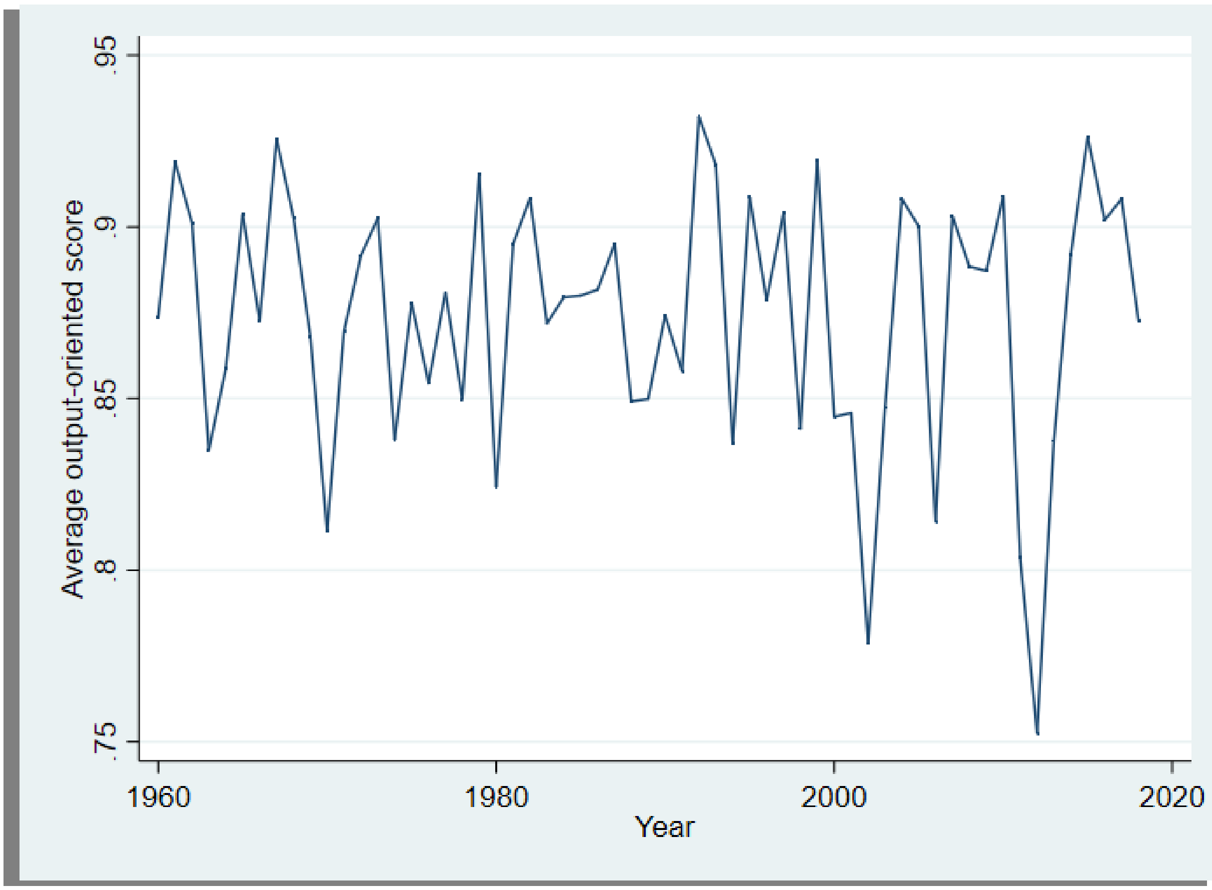
The idea is that very warm days negatively affect the output efficiency score (and consequently the level of production), but it is not as important as other climate factors, such as precipitation. Then, the effect of climate change on agricultural production in the HPA region is more likely to occur through the change in the level (or even variability) of precipitation instead of a change in air temperature.

c. Output and irrigation-oriented efficiency scores

Between 1960 and 2018, the overall output-oriented efficiency score was 0.8738, meaning that counties are producing 87.38% of the efficient level, on average. Similarly, it means that counties are producing 12.62% less than the efficient level. Chen, Dennis and Featherstone (2021) found an overall efficiency score of 85% for wheat farms in Kansas between 2007/08 and 2016/17, which is close to our estimate.

Figure 1 shows the evolution of the mean of the output-oriented efficiency score between 1960 and 2018. Overall, the mean of the output-oriented score in 2018 was the same as in 1960. However, the trajectory was not stable. There are some relevant peaks and troughs during the period. The most relevant trough occurred in 2012, when the average output-oriented score reached a value close to 0.75 – i.e., on average, counties were producing 25% less than the efficient level in 2012. The highest peak was observed in 1992, when the output-oriented efficiency score was 0.93, approximately.

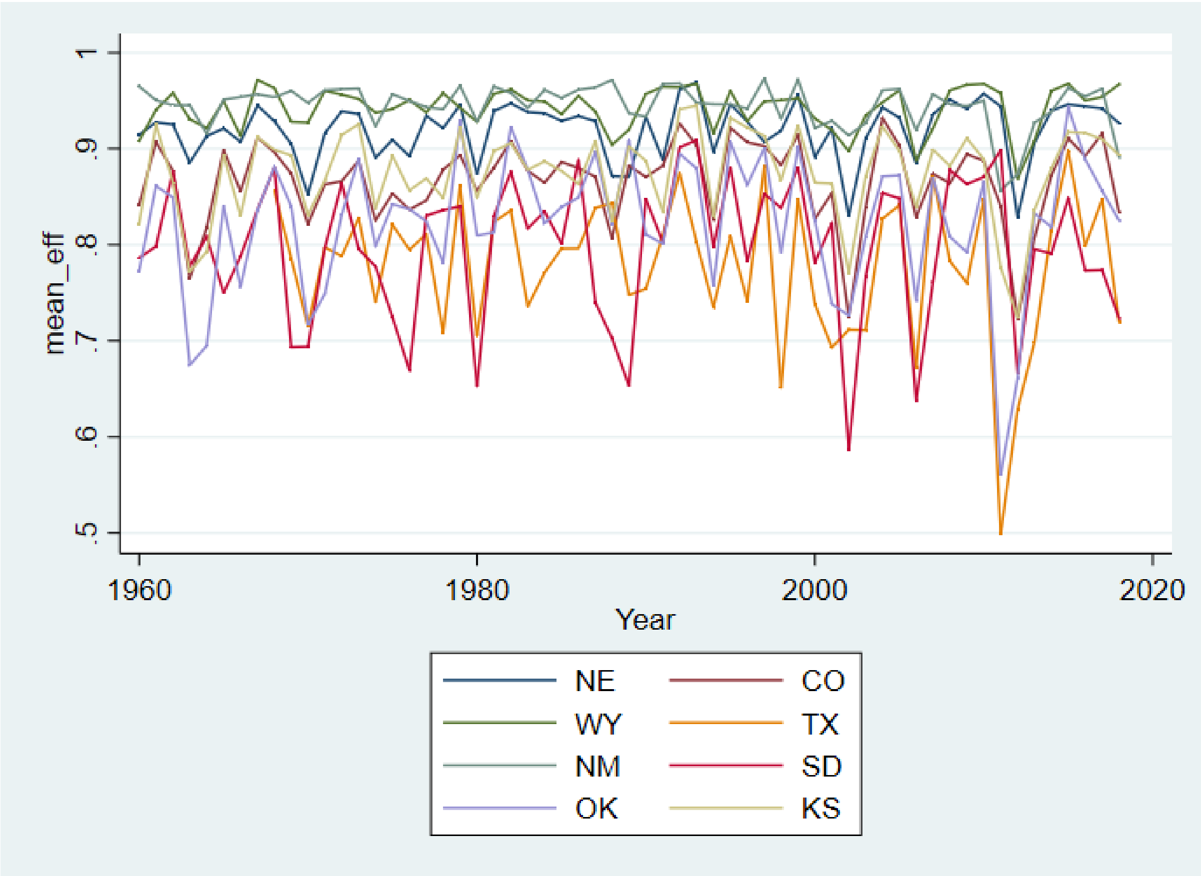
Figure 1 – Evolution of the overall output-oriented score



We also calculate the output efficiency scores by state. New Mexico presented the greatest output-oriented efficiency score in the sample period: 0.95. Wyoming presented the second greatest – 0.94. Nebraska was the other state with output efficiency score greater than 0.90 – it was 0.92. Texas was the state with the lowest output efficiency score in the sample period – around 0.78.

Figure 2 shows the evolution of the output-oriented efficiency score by state. The lowest value was observed in Texas, in 2011 – approximately 0.50. In that same year the second lowest score for the whole series was observed in Oklahoma – 0.56. New Mexico, Wyoming and Nebraska present the most stable series, overall. On the other hand, Texas, South Dakota and Oklahoma appear to have the least stable series.

Figure 2 – Evolution of the overall output-oriented score, by state



Another interesting finding from Figure 2 is that all states presented a negative variation of the output efficiency score between 2017 and 2018, except for New Mexico.

The environmental efficiency score is also calculated. It refers to the efficiency with respect to the share of irrigated land. To calculate the environmental efficiency score, we used Equation

12. Out of 11,629 observations, 2,064 had zero irrigation. Therefore, as explained in the second section, the environmental efficiency score cannot be calculated for these observations. In addition to that, 5,769 observations had negative values for after Equation 12 was applied. For these cases, the efficiency score was denoted as zero.

The mean of the environmental efficiency score was 0.20, meaning that counties could have produced the same level of output and still decrease the share of irrigated land by 80%. South Dakota had score equal to zero in the whole sample period. That is, all counties of South Dakota that are over the High Plains Aquifer could have reduced their shares of irrigated land completely and still kept the same level of production. The greatest environmental efficiency scores were observed in New Mexico (0.54), Wyoming (0.46), and Nebraska (0.28).

In addition, a t-test was performed, and we found that the average output-oriented efficiency score was statistically greater than the average environmental efficiency score, and this was one of the hypothesis of this paper.

5. CONCLUSIONS

This paper aimed to analyze the output-oriented and irrigation-oriented efficiency scores for the High Plains Aquifer area, as well as the impact of climate variables on the technical efficiency scores. The hypothesis of the paper was that the output-oriented score would be greater than the irrigation-oriented efficiency score.

The dataset consists of biomass production and relevant inputs (share of irrigation land, especially) in the counties over the High Plains Area between 1960 and 2018.

Results showed that the overall output-oriented efficiency score was 0.87, meaning that counties are producing 13% less than the efficient amount, on average. This finding is really close to the one reported by Chen, Dennis and Featherstone (2021). They found an overall efficiency score of 85% for wheat farms in Kansas between 2007/08 and 2016/17.

The environmental efficiency score, which is related to the share of irrigated land, was 0.20, on average. That means that the share of irrigated land in the counties over the HPA could have been reduced by 80% while keeping the same level of production.

After perform a t-test, we found that the output-oriented efficiency score was greater than the environmental efficiency score, on average. This was the hypothesis of the paper.

In addition, fertilizers, chemicals, and share of irrigated land presented were positively correlated to agricultural production, as expected. The elasticities of production with respect to fertilizers and chemicals were 0.10 and 0.17, respectively. The semi-elasticity of production with respect to share of irrigated land was 0.30.

Level of annual precipitation, degree-days between -5 and 8 Celsius degrees, and degree-days between 8 and 15 Celsius degrees appeared to increase inefficiency in the counties during the sample period. On the other hand, degree-days above 33 Celsius degree appeared to increase inefficiency in the same period.

For future research, we aim to further develop the calculation of the environmental efficiency score, as well as include other relevant climate variables, such as precipitation variability, in the model. Furthermore, we seek to analyze what is the potential impact of climate change on counties’ production, as well as on the use of irrigation.

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