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ARTICLE

Efficiency and its determinants in the public irrigation projects of Brazil

Eficiência dos regadios públicos no Brasil e os seus determinantes

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Abstract: This paper aims to assess efficiency in the public irrigation projects of Brazil. A Data Envelopment Analysis (DEA) model using a limited set of significant variables and adapted to the specific characteristics of existing public irrigation projects in the country was used. Then a Multiple Regression Analysis was performed to efficient irrigation projects to estimate other inputs that did not have been considered in the DEA model. The results indicate that 15 public projects out of the 34 studied, reached the technical efficiency score, as well as pure efficiency and scale efficiency. The work brings several new contributions to the literature on irrigation management and practical implications for decision makers. It is noteworthy that the results of the study can be useful for a better understanding of the general efficiency of public irrigation and what are its most determining factors.

Keywords: irrigated agriculture, data envelopment analysis, multiple regression.

Resumo: Este artigo pretende e avaliar a eficiência dos regadios públicos no Brasil. Foi usado um modelo de análise envoltória de dados (DEA), com um conjunto limitado de variáveis significantes e adaptadas às caraterísticas específicas dos projetos de regadio existentes. Depois, foi aplicado um modelo de análise regressão múltipla aos projetos de regadio eficientes, para estimar os inputs que não foram considerados no modelo de DEA. Os resultados indicam que 15 projetos entre os 34 estudados atingem a eficiência técnica, bem como a eficiência pura e a eficiência de escala. O trabalho trás alguns contributos novos para a literatura sobre gestão do regadio e tem implicações práticas para os decisores. Os resultados do estudo podem ser úteis para uma melhor compreensão da eficiêcncia geral do regadio públicoe de quais são os fatores determinantes.

Palavras-chave: agricultura de regadio, análise envoltória de dados, regressão múltipla.

1. Introduction

Irrigated agriculture is very important for agricultural production. In 2012, over the World, there were 324 million hectares equipped for irrigation, from which 275 were irrigated land (Food and Agriculture Organization of the United Nations, 2016). Most of this area is irrigated by surface irrigation methods, which is the most common met hod in small farms and developing countries (Kay, 1986).

The benefits of irrigation on livelihood and welfare of farmers are well known in the literature (Hussain & Hanjra, 2004; Connor et al., 2008; Hanjra et al., 2009; Hussain, 2007; Comas et al., 2012; Burney et al., 2013, 2014; Araujo et al., 2019). In most developing countries, smallholder farming are the main source of agricultural production, and family farms represent over the World 90% of the number of farms and between 50% (Graeub et al., 2016) and 75% (Lowder et al., 2016) of the agricultural land.

In that scope, farmers use large amounts of water, and spite surface irrigation systems are the oldest in the World, they have low efficiency levels for water use, as well as for irrigation infrastructures. Generally, the efficiency of surface irrigation systems is much lower than that of drip, sprinkler and pivot systems (Postel et al., 2001; Strelkoff & Clemmens, 2007).

The evaluation of performance in collective public irrigation projects is often neglected existing few studies in the literature addressed to this issue. In the context of Brazilian public irrigation, the need for assessment studies is particularly important because as in other parts of the World, the collective irrigation services show low levels of performance and efficiency from both operational and financial terms.

Brazil is an extended country with a surface of 851 million ha, where 20% is allocated to the agribusiness. Between 1960 and 1996 the irrigated area grew from 0.45 million hectares to 3.1 million hectares. Considering the existence of suitable lands for irrigation, availability of hydric resources without risk of competing with other water uses and respect for environmental and forestry legislation, Brazil has a potential of irrigation estimated on 29.6 million hectares (Christofidis, 2006).

In Brazil, public projects are important local and regional irrigation hubs, concentrated in the semiarid region, due to low water availability. However, in the last decade, the expansion of areas in operation of public projects has been less than 3 thousand hectares (ha) per year - the pace is much lower than that of the private sector, which makes high investments, for the modernization of projects, through of efficient irrigation methods and systems (micro and localized sprinklers). Public irrigation perimeters reduced their participation in the country's irrigated area from 4.7% in 2003/04 (Secretaria dos Recursos Hídricos, 2006) to 2.4% in 2019. In 2019, there were about 100 thousand ha implemented in public projects, which have not been used in production. The implemented area represents the irrigable area already covered by the irrigation infrastructure, and its underutilization in many public irrigation projects is one of the biggest problems faced by the sector (Agência Nacional de Águas e Saneamento Básico, 2021).

Therefore, most of the irrigation area in Brazil is private (96.2%) and has showed a good performance, mainly due to the irrigation methods used, where the pressure systems dominate (Agência Nacional de Águas e Saneamento Básico, 2021). The remaining 3.8% of irrigated area is associated with the public irrigation projects, which include mainly smallholder farmers. Usually these irrigation projects show low efficiency levels.

Gonçalves et al. (2015) evaluated several public irrigation projects in Brazil, and found a great variation in their performance, which can be attributed to the predominant irrigation systems. According to the findings of that study, micro irrigation systems are predominant on the most performed farms, while surface irrigation systems generally are more associated with lower performance and low levels of efficiency.

Benchmarking techniques are widely used to assess irrigation performance (Malano et al., 2004). These techniques are very useful to support the management system in the identification of strengths and weaknesses and hence to improve organization's performance according to its objectives (Alcón et al., 2017). Benchmarking of collective irrigations is relatively recent and the most used techniques include Principal Component Analysis (PCA), Agglomerative Hierarchical Clustering (AHC) and Quality Index (QI) (Zema et al., 2015; Rodríguez-Dìaz et al., 2008; Córcoles et al., 2010, 2012; Uysal & Atış, 2010; Koç & Bayazit, 2015).

Despite the interest of these studies, just a comparative assessment of key indicators is not enough to identify the factors that most can contribute to improving the performance levels of public irrigation projects (Malano et al., 2004). The efficiency assessment can be used to study the performance of public irrigations. In this scope, Data Envelopment Analysis (DEA) developed by Charnes et al. (1978) is a suitable method widely used to study efficiency. DEA is a non-parametric technique that neither requires to establish a predetermined functional relation between input and output nor a priori information about the weights of inputs and outputs (Zhou et al., 2012; Wang et al., 2017).

DEA has been widely applied to study efficiency in various sectors, including agriculture and irrigation (Khoshroo & Singh, 2021; Abbas et al., 2020; Payandeh et al., 2017; Rakshit & Mandal, 2020; Hesampour et al., 2022). However, its application to irrigation problems is uncommon in the literature, and in the case of collective and public irrigations, it is limited to few studies. For instance, Rodríguez-Dìaz et al. (2008), using a DEA model, identified performance differences between districts in Andalusia (Spain), according to the withdrawal systems, being the most efficient districts those where water was charged per unit consumed. Borgia et al. (2013), showed with DEA and AHC that large and small irrigation projects in Mauritania perform similarly, which indicated a margin for improvements. Frija et al. (2009) used a two-phase approach where they applied a DEA model and a Tobit model in collective irrigations of Tunisia and concluded that management and maintenance issues have an important influence on efficiency.

However, despite the advantages of DEA for assessing irrigation performance and efficiency, some caution should be taken. First, the selection of variables used in DEA should be related to the objectives of the study and the productive process (Zema et al., 2018). Second, the use of too many variables as inputs or outputs can lead to erroneous results, where all or almost units analyzed are efficient (Alcón et al., 2017).

Thus, this paper aims to assess efficiency in the public irrigation projects of Brazil. In the first stage, a DEA analysis is performed using a limited and significant set of input and output variables. Then a Multiple Regression Analysis is applied to efficient irrigation to estimate other inputs that did not have been considered in the DEA model. This approach allows to benchmark the inefficient irrigation projects with regards the set of variables that were not included in DEA. Thus, with this procedure we can delineat the efficiency of inefficient irrigation projects under an optimization scenario based on the efficient irrigation projects (Zema et al., 2015).

This paper brings some novel contributions to the literature in irrigation management, as well as practical implications for decision-makers. First, it is one of the few studies that addressed the efficiency of public irrigation projects, and the first one for the Brazilian context. Second, a novel approach to optimize the irrigation project-benchmarking, coupling DEA and regression analysis, is proposed. Finally, the results may be useful to decision-makers to have a concrete idea about the overall efficiency of public irrigation projects.

The article is organized as follows. Section 2 is addressed to the methodology, and includes a brief description of the case study, the presentation of some concepts, such as technical efficiency, pure efficiency and scale efficiency, and the specification of DEA model and the regression models used. Section 3 is dedicated to the presentation and discussion of results. Finally, section 4 contains the conclusions and implications.

2. Methodology, Study Area and Indicators

According to the National Agency for Water and Basic Sanitation, in 2019, the gross value of irrigated production in Brazil was around R$55 billion. Among the irrigated crops, 16 crops had an annual value of more than R$1 billion, totaling 8.2 million hectares (Mha) equipped for irrigation. In 35.5% of that area water was reused (2.9 Mha) and in 64.5% water is from springs (5.3 Mha). As referred before, public irrigation projects are mainly addressed to smallholders farmers, and generated 580,000 direct and indirect jobs in 79 projects and 88 municipalities. (Agência Nacional de Águas e Saneamento Básico, 2021).

This study will focus on the 34 public projects in operation that have an irrigated area greater than 1,000 hectares. Since among the 79 projects with production in 2019, only 34 projects produced in irrigated more than 1,000 hectares, totaling 176,000 ha (90% of the total area). The irrigation of rice, sugarcane and other crops irrigated by central pivots were identified as the most expressive groups of crops on a national scale, totaling around 70% of the irrigated area and occurring in a concentrated way in the territory in national and regional poles. (Agência Nacional de Águas e Saneamento Básico, 2021). By 2040, a greater participation of central pivots and localized irrigation is expected in the demands for irrigated agriculture since they are more efficient in using water (Agência Nacional de Águas e Saneamento Básico, 2021). The following tables present the main data of the public irrigation projects.

Table 1 shows the structural characteristics of public irrigation projects in Brazil, related to location, age, management entity, total area, equipped area, irrigated area, revenue, water use (in m3/s). It is observed that, due to the relationship between equipped area and irrigated area, many perimeters still have a great capacity for expansion in the short term, such as those of Formoso/BA, Tabuleiros de Russas/CE and Baixo Acaraú/CE. On the other hand, other perimeters already show greater use of their equipped area, such as those of S. Nilo Coelho/BA, Luiz Alves do Araguaia/GO and Platôs de Neópolis/SE.

Table 1. Structural features of the public irrigation projects in Brazil

Irrigation Project	State	Age of the project (years)	Management entity	Total area (ha)	Equipped area (ha)	Irrigated area (ha)	Revenue (million $R)	Water use (m3/s)
1. Boacica	Alagoas	37	Codevasf	5484	2762	2299	14	4.9
2. Itiúba	Alagoas	43	Codevasf	1296	900	1198	7	1.1
3. S.Nilo Coelho	Bahia	37	Codevasf	55525	23486	21797	2	70.4
4. Tourão	Bahia	42	Codevas	14567	14677	14677	134	65.0
5. Formoso	Bahia	32	Codevasf	15505	11772	8337	246	106.0
6. Curaçá	Bahia	41	Codevasf	15234	4708	4708	160	65.0
7. Maniçoba	Bahia	41	Codevasf	11786	4847	3913	156	65.0
8. Salitre	Bahia	23	Codevasf	67400	5009	3601	79	65.0
9. São Desidério/ Barreiras Sul	Bahia	43	Codevasf	4322	1934	1934	12	102.0
10. Mirorós	Bahia	25	Codevasf	4870	1772	1701	20	106.0
11. Vaza Barris	Bahia	48	DNOCS	11677	1487	1487	23	106.0
12. Brumado	Bahia	35	DNOCS	8302	4313	1509	19	106.0
13. Jaguaribe Apodi	Ceará	32	DNOCS	9606	5658	5658	31	3.9
14. Baixo Acaraú	Ceará	20	DNOCS	13909	8439	5277	65	3.9
15. Curu-Paraipaba	Ceará	47	DNOCS	6913	3357	2733	16	3.9
16. Tabuleiros de Russas	Ceará	17	DNOCS	18915	10766	2055	42	3.9
17. Morada Nova	Ceará	51	DNOCS	11166	4474	1268	1	3.5
18. Luiz Alves do Araguaia	Goiás	21	Goiás State	8148	2742	2742	24	7.4
19. Jaiba - Etapa I	M. Gerais	46	Codevasf	32754	21889	13348	248	77.2
20. Gorutuba	M.Gerais	43	Codevasf	8487	4800	1583	34	92.5
21. Varzeas de Sousa	Paraíba	15	Paraíba Stat.	6336	4404	1600	5	1.8
22. Caraíbas/Fulgêncio	Pernambuco	23	Codevasf	33437	4728	4728	55*	34.8
23. Icó-Mandantes	Pernambuco	27	Codevasf	26097	2187	2187	25*	34.8
24. Bebedouro	Pernambuco	53	Codevasf	7484	2418	1892	49	34.8
25. Brígida	Pernambuco	27	Codevasf	8685	1436	1436	17*	34.8
26. Platôs de Guadalupe	Piauí	28	DNOCS	3196.2	3106	2080	36	6.4
27. Baixo Açu	R.G. Norte	27	DNOCS	6000	5168	2099	24*	1.1
28. Arroio Duro	R. G do Sul	54	MDR	58623	20406	20406	181	272.2
29. Chasqueiro	R. G. do Sul	36	MDR	25738	19619	7314	14	275.2
30. Platô de Neópolis	Sergipe	26	Sergipe Stat.	10432	7230	6860	80*	2.5
31. Betume	Sergipe	43	Codevasf	8481	4671	4671	9	2.4
32. Cotinguiba/Pindoba	Sergipe	39	Codevasf	3085	2232	1798	6	2.5
33. Rio Formoso	Tocantins	41	Tocant. Stat.	27787	23000	20000	250	20.7
34. São João	Tocantins	11	Tocant. Stat.	5139	3027	1048	7	3.0

Note: *Estimated values
Source: Prepared by the author, based on Agência Nacional ds Águas e Saneamento Básico, 2021.

Table 2. Share of irrigated crops area and water use per crop and ha at the public irrigation projects in Brazil

	% of irrigated area				Water use per crop (m3/s)			
Irrigation Project	Rice	Sugar cane	Other crops with pivot	Other crops	Rice	Sugar cane	Other crops with Pivot	Other crops
1. Boacica	44.7	55.3	0.0	0.0	1.000	8.100	0.500	0.500
2. Itiúba	97.1	1.1	0.0	1.8	1.000	8.000	1.000	1.000
3. Sen. Nilo Coelho	0.0	0.0	1.2	98.8	0.100	5.600	70.400	70.400
4. Tourão	0.0	42.6	1.0	56.4	0.000	9.900	106.000	106.000
5. Formoso	0.0	0.0	6.4	93.6	0.000	9.900	106.000	106.000
6. Curaçá	0.0	42.6	1.0	56.4	0.000	9.900	106.000	106.000
7. Maniçoba	0.0	42-6	1.0	56.4	0.000	9.900	106.000	106.000
8. Salitre	0.0	42.6	1.0	56.4	0.000	9.900	106.000	106.000
9. São Desidério/ Barreiras Sul	0.0	0.0	8.63	9.4	0.000	9.900	106.000	106.000
10. Mirorós	0.0	0.0	0.3	99.7	0.000	9.900	106.000	106.000
11. Vaza Barris	0.0	0.0	0.0	100.0	0.000	9.900	106.000	106.000
12. Brumado	0.0	0.0	0.0	100.0	0.000	9.900	106.000	106.000
13. Jaguaribe Apodi	1.0	0.0	3.2	67.0	2.300	1.300	3.900	3.900
14. Baixo Acaraú	0.0	0.0	1.2	98.8	2.300	1.300	3.900	3.900
15. Curu-Paraipaba	0.0	0.0	2.3	97.7	2.300	1.300	3.900	3.900
16. Tabuleiros de Russas	2.6	0.0	27.9	69.5	2.300	1.300	3.900	3.900
17. Morada Nova	25.9	0.0	20.6	53.5	2.300	1.300	3.900	3.900
18. Luiz Alves do Araguaia	92.3	0.0	1.3	6.4	5.100	5.900	34.400	34.400
19. Jaiba - Etapa I	0.0	19.2	12.2	68.6	0.300	12.700	92.500	92.500
20. Gorutuba	0.0	0.0	0.00	100.0	0.300	12.700	92.500	92.500
21. Varzeas de Sousa	0.0	0.0	53.0	47-0	0.000	0.000	1.800	1.800
22. Caraíbas/Fulgêncio	0.0	0.0	0-8	99.2	0.200	1.300	34.800	34.800
23. Icó-Mandantes	0.0	0.0	0.5	99.5	0.200	1.300	34.800	34.800
24. Bebedouro	0.0	0.0	1.2	98.8	0.200	1.300	34.800	34.800
25. Brígida	0.0	0.0	4.1	95.9	0.200	1.300	34.800	34.800
26. Platôs de Guadalupe	0.0	0.0	26.7	73.3	1.700	2.100	6.400	6.400
27. Baixo Açu	91.7	0.0	0.7	0.076	0.300	0.600	10.000	10.000
28. Arroio Duro	97.9	0.0	0.0	2.1	277.700	0.000	16.400	16.400
29. Chasqueiro	99.0	0.0	0.0	1.0	277.700	0.000	16.400	16.400
30. Platô de Neópolis	17.3	44.1	2.0	36.6	2.300	1.300	3.900	3.900
31. Betume	94.6	0.0	0.0	5.4	2.300	1.300	3.900	3.900
32. Cotinguiba/Pindoba	72.2	9.9	3.1	14.8	2.300	1.300	3.900	3.900
33. Rio Formoso	99.6	0.0	0.0	0.4	20.800	0.700	3.000	3.000
34. São João	0.0	0.0	26.9	73.1	20.800	0.700	3.000	3.000

Source: Prepared by the author, based on Agência Nacional ds Águas e Saneamento Básico, 2021.

In large public projects, the common infrastructure is managed by independent entities, which can be private as Codevasf and DNOCS or public as State autorities. They manage the distribution and collection of water and guarantee the terms of the grant of the irrigators who occupy family or business lots are respected (Agência Nacional de Águas e Saneamento Básico, 2021). Table 2 shows the share of irrigated crops area and water use per crop and ha at the public irrigation projects in Brazil. The irrigation projects presenting the highest shares of rice (% of irrigated area) are Chasqueiro (99.0%), Arroio Duro (97.9%) in the State do Tocantins, and Rio Formoso (99.6%), with good growth prospects in other states, such as Goiás, Mato Grosso do Sul, Maranhão, Piauí, Alagoas and Sergipe, and others.

Table 3 presents, for all variables considered in the efficiency analysis, the descriptive statistics: mean, (STD) Standard Deviation, Coefficient of variation, Maximum and Minimum, calculated. Mean age of the public irrigation projects is 34.5 years, being the maximum age 54 years and the minimum age 11 years. However, despite the great difference between the maximum and minimum age, the other statistical measures (standard deviation: 11.2 and the coefficient of variation: 0.324) do not demonstrate a great dispersion on the age among the public projects.

The mean total area of public irrigation projects is 16364.3 (ha); standard deviation: 16047.7 and the coefficient of variation: 0.981, demonstrating that the mean total area is dispersed among public projects. The same occurred with the mean equipped area investigated, around 7159.5 (ha); standard deviation: 6728.2 and coefficient of variation: 0.940 (is also heterogeneous). Irrigated area presents a mean of 5292.5 (ha); standard deviation: 5751.0; coefficient of variation: 1,087. These values show that the mean irrigated area is heterogeneous among public projects, and represents almost 74% of the mean equipped area and 32% of the mean total area.

Table 3. Descriptive statistics

	Mean	STD	Coefficient of variation	Max	Min
Age of the project (years)	34.5	11.2	0.324	54.0	11.0
Total area (ha)	16364.3	16047.7	0.981	67400.0	1296.0
Equipped area (ha)	7159.5	6728.2	0.940	23486.0	900.0
Irrigated area (ha)*	5292.5	5751.0	1.087	21797.0	1048.0
Revenue (million $R)*	107.2	262.6	2.450	1555.0	1.0
Percentage of irrigated area:					
Rice	24.6%	39.2%	1.595	99.6%	0.0%
Sugar cane	8.8%	17.2%	1.952	55.3%	0.0%
Other crops with pivot	9.3%	18.2%	1.965	86.3%	0.0%
Other crops	57.2%	38.2%	0.667	100.0%	0.0%
Water use per crop (m3/s):					
Rice	18.4	65.0	3.530	277.7	0.0
Sugar cane	4.8	4.4	0.923	12.7	0.0
Other crops with Pivot	43.3	44.1	1.019	106.0	0.5
Other crops	43.3	44.1	1.019	106.0	0.5
Water use (m3/s)	52.5	67.1	1.279	275.2	1.1

* Output parameters

The same is observed with the estimated mean revenue of the projects, which is around R$ 107.2 million; standard deviation: 262.6; coefficient of variation: 2,450 and maximum: 1555.0. Rice is the crop with the highest mean share on the irrigated area (24.6%), being the respective maximum and minimum values 99% and 0%. The standard deviation and coefficient of variation values show also a great dispersion of the weight of rice on irrigated area among the public projects. The high weight of other crops on the irrigated area may indicates a diversified crop patters among the Brazilian public irrigation projects. Water use per crop also presents a pattern similar to the percentage of crop on irrigated area. For total water use, the mean is 52.5 m3/s, and maximum and minimum values are 272.2 m3/s and 1.1 m3/s. The values of standard deviation (67.1) and coefficient of variation (1,279), confirm the existence of a great heterogeneity in the water use among the public irrigation projects.

2.1. Data Envelopment Analysis (DEA)

Farrell (1957) defined the efficiency of a firm as its success in producing as large as possible output from a given set of inputs. This is a very general idea of efficiency since, in a firm, performance can be evaluated according to different efficiency measures, such as technical efficiency (TE), allocative efficiency (AE), economic or cost efficiency (EE), overall technique efficiency (OTE), pure technical efficiency (PTE) and scale efficiency (SE) (Pereira & Marques, 2017).

There are several parametric and non-parametric techniques to measure efficiency. DEA is one of the most used non-parametric techniques. As referred before, DEA compared with parametric techniques has the advantage that it requires neither the definition of a functional relationship between inputs and outputs nor a priori information about the weights of inputs and outputs.

Despite the literature having few applications of DEA to irrigation, there are various applications to measure the efficiency and productivity of agricultural systems (Nassiri & Singh, 2009; Mobtaker et al., 2012; Raheli et al., 2017).

DEA is a linear programming technique developed by Charnes et al. (1978) and has been used in the estimation of production functions and relative efficiency. DEA compares each decision-making unit (DMU) with its relative best producer, which is a unit that obtained more output with the same input or obtained the same output with less input (Farrell, 1957). Each DMU is assigned with a score between 0 and 1, meaning 1 that the DMU is efficient. For a DMU, the difference between 1 and the assigned score shows the amount of input that can be saved or the increase in output that can be obtained given a certain input. The former is an input-oriented optimization problem and the latter is an output-oriented optimization problem.

For this study, a DMU is a given public irrigation project, and the DEA model is formulated as an input-oriented optimization problem. The input-orientation approach was used because we considered only two outputs, namely, irrigated area and agricultural revenue. As one of the DEA limitations is the possibility of existing more efficient DMUs as the number of the variables analyzed is higher, we limited the inputs considered to four variables, which include the age of the irrigation project, total area, and equipped area and water use (Table 4).

Table 4. Inputs, Outputs and Decision Making Units (DMU) used in the efficiency analysis

Parameters / performance indicators	Public Irrigation Projects (DMU)	
Output	1. Boacica	18. Luiz Alves do Araguaia
1. Irrigated area (ha);	2. Itiúba	19. Jaiba - Etapa I
2. Revenue (million $R)	3. Sen. Nilo Coelho	20. Gorutuba
Input	4. Tourão	21. Varzeas de Sousa
1. Age of the project (years)	5. Formoso	22. Caraíbas/Fulgêncio
2. Total area (ha) - DMU	6. Curaçá	23. Icó-Mandantes
3. Equipped area (ha)	7. Maniçoba	24. Bebedouro
4. Water use (m3/s)	8. Salitre	25. Brígida
Percentage of irrigated area:	9. São Desidério/ Barreiras Sul	26. Platôs de Guadalupe
1. Rice	10. Mirorós	27. Baixo Açu
2. Sugar cane	11. Vaza Barris	28. Arroio Duro
3. Other crops with pivot	12. Brumado	29. Chasqueiro
4. Other crops	13. Jaguaribe Apodi	30. Platô de Neópolis
Water use per crop (m3/s):	14. Baixo Acaraú	31. Betume
5. Rice	15. Curu-Paraipaba	32. Cotinguiba/Pindoba
6. Sugar cane	16. Tabuleiros de Russas	33. Rio Formoso
7. Other crops with Pivot	17. Morada Nova	34. São João
8. Other crops		

Table 4 details the inputs, outputs and DMU used in the efficiency analysis. The share of crop areas on irrigated area and water use per crop were not considered in the DEA model, but are included in the efficiency analysis as inputs. As explained above, their values can be estimate for inefficient DMU from efficient DMU as linear combinations.

2.1.1. Technical Efficiency (TE)

Coelli et al. (2005) defined TE as the ability of a firm to produce a given level of output using a feasible amount of inputs. It can be expressed by the ratio of the sum of weighted outputs and the sum of weighted inputs:

$$TE_j = \frac{\sum_{r=1}^{n} u_r y_{rj}}{\sum_{s=1}^{m} v_s x_{sj}} \quad (1)$$

where, x and y are matrices of inputs and outputs, u and v are the respective weights, s is the number of inputs, r is the number of outputs and j is the j^{th} DMU. In this scope, Overall Technical Efficiency (OTE) measures TE under the assumption of constant returns to scale (CRS).

Equation 1 can be transformed into a linear programming model, as follows:

$$\begin{aligned} & Max\,\theta = \sum_{r=1}^{n} u_r y_{rj} \\ & s.t. \\ & \sum_{s=1}^{m} v_s x_{sj} = 1 \\ & \sum_{r=1}^{n} u_r y_{rj} - \sum_{s=1}^{m} v_s x_{sj} \le 0 \\ & u_r \ge 0, v_r \ge 0 \quad and \quad j = \{1,2,3,\ldots k\} \end{aligned} \quad (2)$$

where, θ represents the OTE. This is the Charnes et al. (1978) (CCR) DEA model, which considers constant returns to scale (CRS). Under this model, an increase in inputs results in a proportional increase in outputs.

2.1.2. Pure Efficiency (PTE)

For evaluating PTE, the efficiency frontier is obtained under the assumption of variable returns to scale (VRS). It measures OTE without considering Scale efficiency (SE) and reflects the performance of organizing inputs in the production process (Kumar & Gulati, 2008). PTE can be evaluated by using the BCC DEA model (Banker et al., 1984). This model considers variable returns to scale (VRS), which means that a change in inputs results in an increasing or decreasing change in outputs. Thus, the following linear program can express PTE:

$$\begin{aligned} & Max\,z = \sum_{r=1}^{n} u_r y_{r0} - u_0 \\ & s.t. \\ & \sum_{s=1}^{m} v_s x_{s0} = 1 \\ & \sum_{r=1}^{n} u_r y_{rj} - \sum_{s=1}^{m} v_s x_{sj} - u_0 \le 0 \\ & u_r \ge 0, v_r \ge 0,\ u_0 \text{ free in sign and } \ j = \{1,2,3,\ldots k\} \end{aligned} \quad (3)$$

2.1.3. Scale Efficiency (SE)

Scale efficiency is measured as the ratio between OTE and PTE and gives us information about scale characteristics. It shows the effect of DMU size on efficiency, indicating that some of the inefficiency is due to an inadequate DMU size. In that scope, if the DMU moves to the optimal size, efficiency can be improved considering the same methodology.

A DMU that is technical and pure efficient is operating at the most suitable scale, and hence SE=1. Thus, SE is calculated as follows:

$$SE = \frac{OTE}{PTE} \tag{4}$$

2.2. Estimation of the remaining variables by regression analysis

As DEA was applied to a limited set of variables, it is necessary estimate the value of the remaining variables for the inefficient DMU having as depart point the efficient DMU. In the literature, some techniques can achieve this objective. For instance, Zema et al. (2018) built predictive models between the variables used in DEA and the remaining variables to be predicted. As many pairs of variables were strongly correlated and hence collinear, they used a Principal Component Analysis (PCA). In turn, the extracted PC were used in a Multiple Regression Analysis as predictors of the remaining variables.

Inspired in that model we established several multiple regressions between the some variables used in DEA and the remaining variables for the efficient DMU. Each regression model was establish as linear combination of the remaining variables. After having established the regression equations for the efficient DMU, this regression model can be used to estimate the efficient value of the remaining variables in the inefficient DMU.

As referred before the variables related to the percentage of the areas of rice, sugarcane, other crops irrigated with pivot and other crops on the irrigated area, as well as the respective amounts of water use were not considered in DEA. Thus, we established a multiple regression analysis for the efficient DMU considering as dependent variable the each crop area as independent variables some variables used in DEA, such as the age of the irrigation project, equipped area, irrigated area, revenue, total water use and the water used in the respective crop area.

Afterwards, having predicted the efficient value the crop area for inefficient DMU, the respective values of water use can be obtained directly since they are linearly dependent on crop areas.

3. Results

3.1. Correlations among variables

To measure the correlations among variables, the Spearman Correlation Coefficient (ρ) was used, which neither requires the assumption that the relationship between the variables is linear nor that they are quantitative - it is used to verify the relationship between variables measured at the ordinal level. Spearman's coefficient ρ varies among -1 and 1. The closer you are to these extremes, the greater the association among the variables (Table 5). The negative sign of the correlation means that the variables vary in the opposite direction (Spearman, 1907).

Table 5 shows that the correlation coefficient between irrigated area and the equipped area is 0.91. There are also important positive correlations between total area, and equipped area (0.62) and irrigated area (0.65). The revenue shows a positive correlation with total area (0.53), equipped area (0.59) and irrigated area (0.67). The remaining variables, with exception of the percentage of irrigated area with rice and other crops (0.83), water use in sugar cane and water use in coffee, other crops with pivot and other crops, present weak correlations between variables.

Table 5. Correlation coefficients

	Age of the project (years)	Total area (ha)	Equipped area (ha)	Irrigated area (ha)	Revenue (million $R)	% of irrigated area				Water use (m3/)				Total (m3/s)
						Rice	Sugar cane	Other crops with pivot	Other crops	Rice	Sugar cane	Other crops with Pivot	Other crops	
Age of the project	1.000													
Total area	0.065	1.000												
Equipped area	0.214	0.619	1.000											
Irrigated area	0.300	0.645	0.909	1.000										
Revenue	0.252	0.356	0.584	0.604	1.000									
Percentage of irrigated area:														
Rice	0.202	0.039	0.243	0.230	0.022	1.000								
Sugar cane	0.051	0.204	0.065	0.137	0.405	-0.212	1.000							
Other crops with pivot	-0.178	-0.246	-0.169	-0.220	-0.209	-0.269	-0.194	1.000						
Other crops	-0.150	-0.002	-0.198	-0.191	-0.086	-0.838	-0.091	-0.142	1.000					
Water use:														
Rice	0.220	0.397	0.491	0.385	0.129	0.497	-0.134	-0.128	-0.407	1.000				
Sugar cane	0.250	0.037	-0.024	-0.003	0.302	-0.339	0.387	-0.051	0.221	-0.292	1.000			
Other crops with Pivot	0.215	0.180	0.021	0.065	0.319	-0.463	0.406	-0.059	0.347	-0.190	0.898	1.000		
Other crops	0.215	0.180	0.021	0.065	0.319	-0.463	0.406	-0.059	0.347	-0.190	0.898	1.000	1.000	
Total water use	0.352	0.442	0.461	0.380	0.258	0.166	-0.015	-0.128	-0.110	0.809	0.237	0.394	0.394	1.000

3.2. DEA results

Table 6 presents the results of the DEA model for the overall technical efficiency (OTE), pure efficiency (PTE) and scale efficiency (SE). Results indicate that 15 public irrigation projects on the 34 studied reached the OTE, 20 reached the PTE and 16 are SE, being the following irrigation projects simultaneously OTE and PTE: Itiúba, Senador Nilo Coelho, Tourão, Formoso, Curaçá, Maniçoba, Jaguaribe Apodi, Baixo Acaraú, Platôs de Guadalupe, Baixo Açu, Arroio Duro, Platôt de Neopolis, Bitumen, Rio Formoso and São João. The results also revealed that the Tabuleiros de Russas project reached the SE, but is inefficient in terms the OTE and PTE since its score in both cases is only 0.9. However, there are 5 irrigation projects, that are inefficient for OTE, and only achieved PTE: Mirorós, Luiz Alves do Araguaia, Varzeas de Sousa, Caraíbas/Fulgencio and Brígida. Thus, there are 19 public irrigation projects on the 34 studied, which are not efficient.

Table 6. Technical, pure and scale efficiency per public irrigation project

Irrigation Project	Technical Efficiency	Pure Efficiency	Scale Efficiency	Irrigation Project	Technical Efficiency	Pure Efficiency	Scale Efficiency
1. Boacica	0.66	0.80	0.83	18. Luiz Alves do Araguaia	0.95	1.00	0.95
2. Itiúba	1.00	1.00	1.00	19. Jaiba - Etapa I	0.78	0.80	0.98
3. Senador Nilo Coelho	1.00	1.00	1.00	20. Gorutuba	0.28	0.46	0.61
4. Tourão	1.00	1.00	1.00	21. Varzeas de Sousa	0.32	1.00	0.32
5. Formoso	1.00	1.00	1.00	22. Caraíbas/Fulgêncio	0.98	1.00	0.98
6. Curaçá	1.00	1.00	1.00	23. Icó-Mandantes	0.87	0.98	0.89
7. Maniçoba	1.00	1.00	1.00	24. Bebedouro	0.70	0.71	0.98
8. Salitre	0.81	0.96	0.84	25. Brígida	0.68	1.00	0.68
9. São Desidério/ Barreiras Sul	0.77	0.81	0.95	26. Platôs de Guadalupe	1.00	1.00	1.00
10. Mirorós	0.72	1.00	0.72	27. Baixo Açu	1.00	1.00	1.00
11. Vaza Barris	0.72	0.78	0.93	28. Arroio Duro	1.00	1.00	1.00
12. Brumado	0.17	0.45	0.38	29. Chasqueiro	0.39	0.44	0.88
13. Jaguaribe Apodi	1.00	1.00	1.00	30. Platô de Neópolis	1.00	1.00	1.00
14. Baixo Acaraú	1.00	1.00	1.00	31. Betume	1.00	1.00	1.00
15. Curu-Paraipaba	0.67	0.69	0.98	32. Cotinguiba/Pindoba	0.55	0.87	0.64
16. Tabuleiros de Russas	0.90	0.90	1.00	33. Rio Formoso	1.00	1.00	1.00
17. Morada Nova	0.06	0.38	0.17	34. São João	1.00	1.00	1.00

The summarized statistics for the three estimated measures of efficiency considering total DME and inefficient are presented in Table 7. Mean OTE is 0.79, with a standard deviation of 0.27, and maximum and minimum scores of 1 and 0.06. In relation to the PTE the mean score is 0.88, with a standard deviation of 0.19, and maximum and minimum values of 1 and 0.38. For the SE the mean score is 0.87, with a standard deviation of 0.21, and ranging from 0.17 to 1. These values revealed a significant variability around the mean, indicating a great heterogeneity in the performance among the public irrigation projects in Brazil.

Table 7. Mean technical, pure and scale efficiency

	Mean	STD	Max.	Min.
	Total DMU			
Overall Technical Efficiency	0.79	0.27	1.00	0.06
Pure Efficiency	0.88	0.19	1.00	0.38
Scale Efficiency	0.87	0.21	1.00	0.17
Inefficient DMU				
Overall Technical Efficiency	0.63	0.28	0.98	0.06
Pure Efficiency	0.72	0.19	0.98	0.38
Scale Efficiency	0.76	0.24	0.98	0.17

The inefficient DMU presents mean scores of OTE, PTE and SE of 0.63, 0.72 and 0.76, being the respective minimum scores of 0.06, 0.38 and 0.17. Thus, on average the inefficient irrigation projects need to use approximately a third less of the inputs than currently maintaining the same level of outputs to achieve the efficiency standards.

Among the most inefficient DMU we can find the following irrigation projects: Morada Nova, Luiz do Araguaia, Gortuba, Varzeas de Sousa, Chasqueiro and Brumado. The irrigation project of Morada Nova in the State of Ceará is the least efficient DMU for the three measures of efficiency considered, and the project of Brumado in the State of Bahia is among the least three efficient DMU for PTE and SE.

Table 8 presents the values of some performance indicators for efficient and inefficient DMU, as well as the percentage differences between them. The age of projects seems do not have any influence on its efficiency. In the efficient DMU, the percentage of the equipped area on the total area and the percentage of the irrigated area on the equipped area are, on average, 38% and 26% higher than in the inefficient DMU. These figures might suggest that inefficient DMU may have some conception problems, as well as farmers having difficulties in adopting irrigation techniques or even a lack of profitability of irrigated crops in that areas. Water use is another variable that reveals differences in performance between efficient and inefficient DMUs since the former on average use 26% less water than the latter. The ratios Revenue/ equipped area and Revenue/water use also are much more favorable to efficient DMU than to inefficient DMU. The inefficient DMU to achieve efficiency should at least increase the Revenue/ equipped area on 30% and the Revenue/water used in 68%.

Table 8. Performance indicators for efficient and inefficient DMU

	Efficient	inefficient	%Δ
Mean age of the project (years)	34.5	34.53	0.0
Equipped area/total area (ha/ha)	0.549	0.342	38%
Irrigated area/equipped area (ha/ha)	0.870	0.559	36%
Water use (m3/s)	45.91	57.74	-26%
Revenue/equipped area($R/ha)	9834.8	6870.2	30%
Revenue/water used(Million $R/m3/s)	2.015	0.6409	68%

3.3. Estimation of the remain variables using regression analysis

In the following Table 9 is presented the coefficients of the linear regression models used to estimate crop areas for efficient DMU. In general, we can say that the estimated models show a good explanatory capacity. The adjusted square R is 70.1%, 78.1% and 48.5% in the models that predict the areas of rice, sugarcane and other crops. The model that predicts the area of other crops irrigated with pivot has a low explanatory capacity, and most of the coefficients are not statistically significants.

For the model that predicts the area of rice, the coefficients of revenues, total water use and water use in rice are statistically significant at a 10% and at a 1% level. Both, revenue and water use in rice are associated with an increase on the area of rice, while total water use has a negative effect. In the case of sugarcane, the statistically significant variables are equipped area ($p < 0.1$), total water use ($p < 0.1$) and water used in sugarcane ($p < 0.05$). However, only the latter has a positive effect the crop area. Finally, the model that predicts the area of other crops, where the statistically significant variables are revenue ($p < 0.01$) and water use in other crops ($p < 0.01$). The former has a negative influence on the area of other crops and the latter a positive influence.

Table 9. Coefficients of linear regression models used to estimate crop areas for efficient DMU

	Dependent Variables			
	Irrigated area			
	Rice	Sugarcane	Other crops with pivot	Other crops
Independent variables:				
Age of the project	66.48	-25.45	-6.90	-36.63
Equipped area	0.17	-0.61*	-0.01	0.83
Irrigated area	0.08	0.71*	-0.01	-0.15
Revenue	24.67*	6.15	-0.03	-40.14***
Total water use	-64.17***	-12.39*	-0.66	-18.60
Water use in rice	96.53***	-	-	-
Water use in sugar cane	-	131.68**	-	-
Water use in crops with pivot	-	-	-1.104	-
-Water use in other crops	-	-	-	19.11***
Constant	2069.56	1007.91	505.60	-240.26
Explanatory capacity	70.1%	48.5%	6.8%	78.1%

Notes: * - p < 0.1; ** - p < 0.05; *** - p < 0.01

Table 10 presents the mean non-efficient and efficient values for inefficient DMU. The results indicate that to the inefficient irrigation projects be more efficient the areas of rice and other crops irrigated with pivot should decrease on average 89% and 36%, and the areas of irrigated sugarcane should be abandoned. However, the area with other crops should more than double. This area might include also the areas of drip irrigation for which the disaggregate data are not available per public irrigation project.

Table 10. Mean non-efficient and efficient values of the remaining variables for inefficient DMU

	Irrigated area (ha)			
	Rice	Sugarcane	Other crops with pivot	Other crops
Mean non-efficient values	675	291	279	1779
Mean efficient values	73	0	178	3823
	Water use (m3/s)			
	Rice	Sugarcane	Other crops with pivot	Other crops
Mean non-efficient values	15.49	5.23	48.57	48.57
Mean efficient values	1.70	0.00	30.90	104.40

The changes on the irrigated crop areas will also change the water allocation between crops, being foreseen a proportional decrease on water demand for rice, sugarcane and crops irrigated with pivot, while the demand water in other crops has to increase.

4. Conclusion

This paper assessed the efficiency of public irrigation projects in Brazil by using a Data Envelopment Analysis coupled with a multiple linear regression analysis to predict the efficient value of the variables not included in the efficiency analysis.

The results of Data Envelopment Analysis allow us to conclude that from the 34 public irrigation projects studied, 15 are technical efficient, 20 are pure efficient and 16 are scale efficient. The average values of these efficiencies are 0.79, 0.88 and 0.87, respectively, while the averages values of inefficient decision-making units are 0.63, 0.72 and 0.76, respectively. Regarding the analysis of the remaining variables not included in the efficiency analysis, we can conclude that to the inefficient irrigation projects be more efficient, the areas of rice and other crops irrigated with pivot should decrease on average 89% and 36%, and the areas of irrigated sugarcane should be abandoned. However, the area with other crops should more than double. This area might include also the areas of drip irrigation for which the disaggregate data are not available per public irrigation project.

As main contributions of this study to the literature on irrigation and water management, we highlight the fact that this is one of the few studies addressed to the public irrigation projects, being the first one on the Brazilian context. From a methodological point of view, the use of a multiple regression analysis coupled with Data Envelopment Analysis to estimate the efficient value of the remaining variables not included in the efficiency analysis is also a novelty. Finally, the paper also brings practical contributions to the management of public irrigation projects in Brazil.

References

Abbas, A., Waseem, M., & Yang, M. (2020). An ensemble approach for assessment of energy efficiency of agriculture system in Pakistan. *Energy Efficiency*, *13*, 683-696. http://dx.doi.org/10.1007/s12053-020-09845-9

Agência Nacional de Águas e Saneamento Básico – ANA. (2021). *Atlas irrigação: uso da água na agricultura irrigada*. Brasília: Ministério da Integração Nacional e do Desenvolvimento Regional.

Alcón, F., García-Bastida, P. A., Soto-García, M., Martínez, A., Martin-Gorriz, B., & Baille, A. (2017). Explaining the performance of irrigation communities in a water-scarce region. *Irrigation Science*, *35*, 193-203. http://dx.doi.org/10.1007/s00271-016-0531-7

Araujo, D. F., Costa, R. N., & Mateos, L. (2019). Pros and cons of furrow irrigation on smallholdings in northeast Brazil. *Agricultural Water Management*, *221*, 25-33. http://dx.doi.org/10.1016/j.agwat.2019.04.029

Banker, R. D., Charnes, A., & Cooper, W. W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management Science*, *30*(9), 1078-1092. Retrieved in 2023, August 16, from http://www.jstor.org/stable/2631725

Borgia, C., García-Bola˜nos, M., Li, T., Gómez-Macphersona, H., Comas, J., Connor, D., & Mateos, L. (2013). Benchmarking for performance assessment of small and largeirrigation schemes along the Senegal Valley in Mauritania. *Agricultural Water Management*, *121*, 19-26. http://dx.doi.org/10.1016/j.agwat.2013.01.002

Burney, J. A., Naylor, R. L., & Postel, S. L. (2013). The case for distributed irrigation as a development priority in sub-Saharan Africa. *Proceedings of the National Academy of Sciences of the United States of America*, *110*, 12513-12517. http://dx.doi.org/10.1073/pnas.1203597110

Burney, J., Cesano, D., Russell, J., Lèvre La Rovere, E., Corral, T., Coelho, N. S., & Santos, L. (2014). Climate change adaptation strategies for smallholder farmers in the Brasilian Sertão. *Climatic Change*, *126*, 45-59. http://dx.doi.org/10.1007/s10584-014-1186-0

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research*, *2*(6), 429-444. http://dx.doi.org/10.1016/0377-2217(78)90138-8

Christofidis, D. (2006). Água na produção de alimentos: o papel da academia e da indústria no alcance do desenvolvimento sustentável. *Revista de Ciências Exatas*, *12*(1), 37-46.

Coelli, T., Laewers, L., & Van Huylenbroeck, G. (2005). *Formulation of technical, economic and environmental efficiency measures that are consistent with the materials balance condition*. Brisbane, Australia: University of Queensland, Centre for Efficiency and Productivity Analysis.

Comas, J., Connor, D., Isselmou, M., Mateos, L., & Gómez-Macpherson, H. (2012). Why has small-scale irrigation not responded to expectations with traditional subsistence farmers along the Senegal River in Mauritania? *Agricultural Systems*, *110*, 152-161. http://dx.doi.org/10.1016/j.agsy.2012.04.002

Connor, D. J., Comas, J., Gomez-Macpherson, H., & Mateos, L. (2008). Impact of smallholder irrigation on agricultural production, food supply and economic prosperity of a representative village beside the Senegal River Mauritania. *Agricultural Systems*, *96*, 1-15. https://doi.org/10.1016/j.agsy.2007.04.001.

Córcoles, J. I., de Juan, J. A., Ortega, J. F., Tarjuelo, J. M., & Moreno, M. A. (2012). Evaluation of irrigation systems by using benchmarking techniques. *Journal of Irrigation and Drainage Engineering*, *138*(3), 225-234. http://dx.doi.org/10.1061/(ASCE)IR.1943-4774.0000386

Córcoles, J. I., de Juan, J. A., Ortega, J. F., Tarjuelo, J. M., & Moreno, M. A. (2010). Management evaluation of water users associations using benchmarking techniques. *Agricultural Water Management*, *98*, 1-11. http://dx.doi.org/10.1016/j.agwat.2010.07.018

Farrell, M. J. (1957). The measurement of productive efficiency. *Journal of the Royal Statistical Society. Series A (General)*, *120*(3), 253-290. http://dx.doi.org/10.2307/2343100

Food and Agriculture Organization of the United Nations – FAO. (2016). *AQUASTAT: FAO's Global Information System on Water and Agriculture*. Rome: Food and Agriculture Organization of the United Nations.

Frija, A., Chebil, A., Speelman, S., Buysse, J., & Van Huylenbroeck, G. (2009). Water useand technical efficiencies in horticultural greenhouses in Tunisia. *Agricultural Water Management*, *96*, 1509-1516. http://dx.doi.org/10.1016/j.agwat.2009.05.006

Gonçalves, F. M., Ribeiro, R. S. F., Costa, R. N. T., & Burte, J. D. (2015). A management analysis tool for emancipated public irrigation areas using neural networks. *Water Resources Management*, *29*, 2393-2406. http://dx.doi.org/10.1007/s11269-015-0948-4

Graeub, B. E., Chappell, M. J., Wittman, H., Ledermann, S., Kerr, R. B., & Gemmill-Herren, B. (2016). The State of family farms in the world. *World Development*, *87*, 1-15. http://dx.doi.org/10.1016/j.worlddev.2015.05.012

Hanjra, M.A., Ferede, T., & Gutta, D.G. (2009). Reducing poverty in sub-Saharan Africa through investments in water and other priorities. *Agricultural Water Management*, *96*, 1062-1070. http://dx.doi.org/10.1016/j.agwat.2009.03.001

Hesampour, R., Hassani, M., Hanafiah, M. M., & Heidarbeigi, K. (2022). Technical efficiency, sensitivity analysis and economic assessment applying data envelopment analysis approach: A case study of date production in Khuzestan State of Iran. *Journal of the Saudi Society of Agricultural Sciences*, *21*(3), 197-207. http://dx.doi.org/10.1016/j.jssas.2021.08.003

Hussain, I. (2007). Poverty-reducing impacts of irrigation: evidence and lessons. *Irrigation and Drainage*, *56*(2-3), 147-164. http://dx.doi.org/10.1002/ird.298

Hussain, I., & Hanjra, M. A. (2004). Irrigation and poverty alleviation: review of the empirical evidence. *Irrigation and Drainage*, *53*(1), 1-15. http://dx.doi.org/10.1002/ird.114

Kay, M. (1986). *Surface irrigation systems and practice.* Bedford: Cranfield Press.

Khoshroo, A., & Singh, S. (2021). Measuring economic efficiency of kidney bean production using non-discretionary data envelopment analysis. *Advances in Mathematical Finance and Applications*, *6*(2), 233-244.

Koç, C., & Bayazit, Y. (2015). A study on assessment financing of irrigation schemes. *Irrigation and Drainage*, *64*(4), 535-545. http://dx.doi.org/10.1002/ird.1925

Kumar, S., & Gulati, R. (2008). An examination of technical, pure technical, and scaleefficiencies in Indian public sector banks using data envelopment analysis. *Eurasian Journal of Business and Economics*, *1*(2), 33-69.

Lowder, S. K., Skoet, J., & Raney, T. (2016). The number, size, and distribution of farms, smallholder farms, and family farms worldwide. *World Development*, *87*, 16-29. http://dx.doi.org/10.1016/j.worlddev.2015.10.041

Malano, H., Burton, M., & Makin, I. (2004). Benchmarking performance in the irrigation and drainage sector: a tool for change. *Irrigation and Drainage*, *53*(2), 119-133. http://dx.doi.org/10.1002/ird.126

Mobtaker, H. G., Akram, A., Keyhani, A., & Mohammadi, A. (2012). Optimization of energy required for alfalfa production using data envelopment analysis approach. *Energy for Sustainable Development*, *16*(2), 242-248. http://dx.doi.org/10.1016/j.esd.2012.02.001

Nassiri, S. M., & Singh, S. (2009). Study on energy use efficiency for paddy crop using data envelopment analysis (DEA) technique. *Applied Energy*, *86*(7-8), 1320-1325. http://dx.doi.org/10.1016/j.apenergy.2008.10.007

Payandeh, Z., Kheiralipour, K., Karimi, M., & Khoshnevisan, B. (2017). Joint DEAand life cycle assessment for environmental impact reduction in broiler production systems. *Energy*, *127*, 768-774. http://dx.doi.org/10.1016/j.energy.2017.03.112

Pereira, H., & Marques, R. C. (2017). An analytical review of irrigation efficiency measured using deterministic and stochastic models. *Agricultural Water Management*, *184*, 28-35. http://dx.doi.org/10.1016/j.agwat.2016.12.019

Postel, S., Polak, P., Gonzales, F., & Keller, J. (2001). Drip irrigation for small farmers: a new initiative to alleviate hunger and poverty. *Water International*, *26*, 3-13. http://dx.doi.org/10.1080/02508060108686882

Raheli, H., Rezaei, R. M., Jadidi, M. R., & Mobtaker, H. G. (2017). A two-stage DEA model to evaluate sustainability and energy efficiency of tomato production. *Information Processing in Agriculture*, *4*(4), 342-350. http://dx.doi.org/10.1016/j.inpa.2017.02.004

Rakshit, I., & Mandal, S. K. (2020). A global level analysis of environmental energy efficiency: an application of data envelopment analysis. *Energy Efficiency*, *13*, 889-909. http://dx.doi.org/10.1007/s12053-020-09857-5

Rodríguez-Dìaz, J. A., Camacho, E., López, R., & Pérez, L. (2008). Benchmarking and multivariate data analysis techniques for improving the efficiency of irrigation districts: na application in Spain. *Agricultural Systems*, *96*, 250-259. http://dx.doi.org/10.1016/j.agsy.2007.07.010

Secretaria dos Recursos Hídricos – SRH. (2006). *Tomada de contas anual: exercício de 2005*. Brasília: Ministério do Meio Ambiente.

Spearman, C. E. (1907). Demonstration of Formulae for True Measurement of Correlation. *The American Journal of Psychology*, *18*(2), 161-169. http://dx.doi.org/10.2307/1412408

Strelkoff, T. S., & Clemmens, A. J. (2007). Hydraulics of surface systems. In G. J. Hoffman (Ed.), *Design and operation of farm irrigation systems* (2. ed., pp. 436-498). St. Joseph: American Society of Agricultural and Biological Engineers.

Uysal, Ö. K., & Atış, E. (2010). Assessing the performance of participatory irrigation management over time: a case study from Turkey. *Agricultural Water Management*, *97*(7), 1017-1025. http://dx.doi.org/10.1016/j.agwat.2010.02.007

Wang, J., Lv, K., Bian, Y., & Cheng, Y. (2017). Energy efficiency and marginal carbon dioxide emission abatement cost in urban China. *Energy Policy*, *105*, 246-255. http://dx.doi.org/10.1016/j.enpol.2017.02.039

Zema, D. A., Nicotra, A., Mateos, L., & Zimbone, S. M. (2018). Improvement of the irrigation performance in Water Users Associations integrating data envelopment analysis and multi-regression models. *Agricultural Water Management*, *205*, 38-49. http://dx.doi.org/10.1016/j.agwat.2018.04.032

Zema, D. A., Nicotra, A., Tamburino, V., & Zimbone, S. M. (2015). Performance assessment of collective irrigation in Water Users' Associations of Calabria (Southern Italy). *Irrigation and Drainage*, *64*(3), 314-325. http://dx.doi.org/10.1002/ird.1902

Zhou, P., Ang, B. W., & Zhou, D. Q. (2012). Measuring economy-wide energy efficiency performance: a parametric frontier approach. *Applied Energy*, *90*, 196-200. http://dx.doi.org/10.1016/j.apenergy.2011.02.02

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