Brazilian Journal of Chemical Engineering
https://doi.org/10.1007/s43153-023-00356-5

ORIGINAL PAPER

A data envelopment analysis approach to measuring socio-economic efficiency due to renewable energy sources in Brazilian regions

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Received: 30 September 2022 / Revised: 21 May 2023 / Accepted: 23 May 2023

Abstract
The challenge of reducing CO_2 emissions imposes on the countries the inclusion of renewable energies in their electricity matrix. Brazil needs to improve the participation of Wind, Solar, and Biomass in its system once its electricity generation is highly concentrated on hydro sources. Further, renewable, Electricity generation power plants are frequently associated with good impacts on carbon emission mitigation and job generation. In this paper, we sought to answer if there is a difference in the efficiency of electricity generation technologies' capacity to induce regional socio-economic and environmental development. We used a data envelopment analysis (DEA) approach to measure the relative efficiency scores of Brazilian mesoregions that hold power plants regarding environmental and socio-economic dimensions. Results show that the mesoregions which contain nuclear, wind, and photovoltaic power plants (or a combination of these technologies) perform better than mesoregions that comprise biomass, gas, and coal thermal facilities. In addition, the results show that renewable energy facilities perform better than non-renewable facilities in direct job generation and GDP aggregation. This study contributes to the existing literature from a methodological perspective as we compare different renewable energy technologies in three dimensions (social, economic, and environmental) at a regional level.

Keywords Data envelopment analysis · Renewable electricity sources · Regional social-economic development · Environmental efficiency · Brazil regional efficiency

List of abbreviations

AEP	Annual electricity production
BIGS	Brazilian Institute of Geography and Statistics (*Instituto Brasileiro de Geografia e Estatística*, IBGE).
CAPEX	Capital expenditure
CCR	Constant returns to scale
CCS	Carbon capture and storage
CF	Capacity factor
CO_2	Carbon dioxide
DEA	Data envelopment analysis
DMU	Decision-making units
ERO	Energy research office (*Empresa de Pesquisa Energética*, EPE)
ESO	Electricity system operator (*Operador Nacional do Sistema*, ONS)
FCR	Fixed charge rate
FOC	Fixed annual operating cost
GDP	Gross domestic product
GHG	Greenhouse gas emission
GW	Gigawatt
HDI	Human development index
IEA	International energy agency
IPPC	Intergovernmental panel on climate change
LCOE	Levelized Cost of Energy
MWh	Megawatt hours
NDR	Non-decreasing returns to scale
NIS	National interconnected system (*Sistema Interligado Nacional*, SIN)

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Published online: 12 June 2023

NREL	American national renewable energy laboratory
OPEX	Operational costs
PPP	Purchasing power parities
PROINFA	Program for incentives to alternative energy sources
SEVI	Socio-economic vulnerability index (*Indicador de Nível Socioeconômico*, INSE)
SHP	Small hydro plants (*Pequenas Centrais Hidrelétricas*, PCH)
TCC	Total capital costs
VOC	Variable operating cost
VRS	Variable returns to scale
WACC	Weighted average cost of capital

Introduction

A growing number of countries are announcing the reduction of carbon dioxide (CO_2) and greenhouse gas emissions (GHG) in late years. Nevertheless, according to IEA (2021a), the pledges by governments to achieve net zero emissions by 2050 are far from the minimum required actions necessary to limit the global temperature rise 1.5 °C. Electricity generation is today's single largest source of energy CO_2 emissions, accounting for 36% of total energy-related emissions. In 2020, around 74% of the 12.1 Gt of CO_2 emissions from electricity generation worldwide were related to coal-fired generation IEA (2021a). Fossil fuel-fired plants are the major source of anthropogenic CO_2 emanation, but their usage still plays an important role in meeting the increasing energy demand (Qureshi et al. 2021). Recent studies account for a transition path in the usage of fossil fuels. The coal desulfurization technology, for instance, avoids harmful sulfur pollution in the process of coal utilization. Cai et al. (2021) show promising results with a microwave desulfurization process. Besides coal, gas-fired power plants are responsible for 22% of CO_2 emissions IEA (2021a). Transition paths for this energy source include carbon capture and storage (CCS) techniques (Qureshi et al. 2021). Some technologies that integrate carbon capture and CO_2-to-methanol conversion are achieving satisfying CO_2 emissions reduction (Zhou et al. 2023).

In parallel with technical efforts to an energy transition scenario, IEA (2022) points out the urgency of increasing renewable energy capacity in upcoming years. The global energy crisis faced by Europe in 2022 is an example of the importance of renewable sources in security and production issues (IEA 2022). In 2020, about 26.7% of the generated electricity in the world encompassed renewable sources such as hydro, solar, wind, and biomass. China, the United States, and Germany, for instance, produced 28.5%, 19.2%, and 44% of their electricity using such renewable sources, respectively (IEA 2021b). In this sense, the Brazilian electricity matrix is more sustainable than most countries: in 2021, 85.5% of the generated electricity in the country came from renewable sources (ERO, Energy Research Office — *Empresa de Pesquisa Energética* EPE (2021)). Despite holding a sustainable electricity matrix, Brazil still needs to improve the participation of wind, solar, and biomass in its system once its electricity generation is highly concentrated on hydro sources (56.8%). The dependency on hydroelectricity is leading the country to face supply problems due to the change of the rain regime in the last few years (NSO, Electricity System Operator — *Operador Nacional do Sistema* ONS (2022b)). Therefore, planning the system's expansion to meet the increasing electricity demand with hydroelectricity may cause reliability problems.

The role of renewable energy plants in socioeconomic development is a topic frequently studied by researchers (e.g., Frondel et al. (2010); Simas and Pacca (2014); Andini et al. (2019); Arvanitopoulos and Agnolucci (2020); Gonçalves et al. (2020); Rose et al. (2022); Chachuli et al. (2021); Ibrahim et al. (2021); San Cristóbal (2011)). The implementation of renewable energy facilities tends to be associated with a good impact on job generation Arvanitopoulos and Agnolucci (2020); Frondel et al. (2010), and macroeconomic indicators Andini et al. (2019); Swain and Karimu (2020). Besides, some authors identify indirect effects of renewable electricity facilities, such as an increase in the energy system reliability, the development of a manufacturing cluster in the regions that receive those facilities Rose et al. (2022); Simas and Pacca (2014), and even an improvement in the population's health Miśkiewicz (2020). Regarding the Brazilian case, Gonçalves et al. Gonçalves et al. (2020) found positive significant impacts of wind power electricity facilities on the labor market, similar to the conclusions of Simas and Pacca conclusions Simas and Pacca (2014).

Developing countries such as Brazil witnessed social and economic challenges worsened by the COVID-19 pandemic. According to the World Bank (Bank 2022), Brazil was the most affected country by the pandemic in Latin America, counting more than 22 million reported cases of COVID-19 and more than 600 hundred deaths until January 2022. The Brazilian economy reduced by 3.9% in 2020, forcing 5% of the active population to leave their jobs and raising the unemployment rate from 11.9% to 14.6%. It is important to mention that the pandemic scenario mainly affected the poorest workers, who could not access infrastructure to maintain their jobs remotely (Bank 2022). Inequality in Brazil is a long-term problem that worsened during the pandemic months. As a comparison, the income of the 40% poorest families was reduced by 35%. In the same period, the income of the 60% richest families decreased by 22%. Poverty did not rise more in Brazil due to the Government income transfer program (Bank 2022). The social inequality caused by the pandemic rose sharply in the North and Northeast Brazilian regions, which are historically the country's poorest regions (Bank 2022). These regions, especially the Northeast, have a great potential to receive photovoltaic and wind power plants. As an example, two of the most prominent photovoltaic parks in Brazil are located in the states of Piauí and Bahia (ONS 2022a), both of them in the lowest quantile of the Human Development Index (HDI) in the country (IBGE 2010). The northeast region hosts about 650 wind plants, more than 88% of this source's installed capacity in Brazil.

Following the debate on the importance of renewable electricity sources as socio-economic drivers, this research investigates if there is a difference among energy sources for this purpose. If there is, which renewable energy source is more efficient as a socio-economic inducer? We use the nonparametric Data Envelopment Analysis (DEA) to measure the relative efficiency of the Brazilian mesoregions. Such an approach has been used to evaluate the efficiency of cities, countries, and regions in applying sustainability actions (see, e.g., the literature review of Tsaples and Papathanasiou (2021)). DEA has also been used to measure the efficiency of renewable energy facilities (San Cristóbal 2011; Halkos and Tzeremes 2012; Zeng et al. 2019) and the technical efficiency of countries or regions in using renewable energy (Chachuli et al. 2021; Woo et al. 2015; Chien and Hu 2007). Accordingly, this study contributes to the existing literature from a methodological perspective as we compare different renewable energy technologies in three dimensions (social, economic, and environmental) at a regional level. Most of the related studies analyze the socio-economic and environmental impact regarding the existence of a certain technology type. Further, relative efficiency is mostly applied at a macroeconomic level, comparing power plants.

The results of the DEA evaluation show that renewable electricity sources are more efficient in leading regions where they operate towards socio-economic and environmental development. There is high variability in the efficiency of Brazilian mesoregions where biomass facilities operate due to the high diversity of raw materials used. The mesoregions where wind and photovoltaic facilities are installed are consistently more efficient on socio-economic dimensions.

In this context, an important question arises: May renewable energy sources induce a region's socio-economic development and environmental benefits? If so, which sources are the most efficient in generating these multi-dimension results?If renewable energies can lead to social improvements, policymakers could install them from a regional perspective, not necessarily in the interconnected dispatch system. This approach could also reduce transmission costs.

This paper is organized as follows: Section "Literature review" presents some literature related to the theme. In the following Section, we present the materials and methods used in this research, focusing on describing the scenario of renewable energy sources in Brazil, the Data Envelopment Analysis (DEA) methodology, and data and details about the applied study. Section "Results and discussion" shows the research results and discussions, followed by the conclusions.

Literature review

Implementing renewable energy power plants is frequently associated with a positive impact on job creation. Frondel et al. (2010) mention, for instance, some positive reports from the German Environmental Ministry regarding this topic, which accounted for an increase of 55% of total "green" jobs between 2004 and 2007. In a more recent review, Arvanitopoulos and Agnolucci (2020) mention the German case as an example of job creation through renewable energies.

Arvanitopoulos and Agnolucci (2020) argue that there is evidence that renewable energies positively impact direct, indirect, and induced jobs. These authors classify as direct the jobs created by the sector's core activities and as indirect those related to the energy sector's supply chain. To them, induced jobs are classified as those generated by an increase in the aggregate demand stimulated by the renewable industry.

Rose et al. (2022) amplify the social benefits of installing renewable electricity facilities. Beyond the environmental and job creation benefits, they list indirect effects such as an increase in the energy system reliability and developing a manufacturing cluster in the regions that receive those facilities. Regarding this last topic, Simas and Pacca (2014) highlight that the studies that consider the theoretical number of necessary jobs to implement a renewable facility should consider imports and external market participation in the construction process. Even considering this, these authors found evidence of a positive impact on job generation In Brazilian cities that hold wind farms.

Still, regarding the impact on unemployment rates due to renewable energies, we should expect different effects depending on the project's phase. Rose et al. (2022) estimate that the deployment of additional 7 GW offshore wind facilities in California between 2030 and 2040 is estimated to increase employment by 65,000 and 131,000 job-years during the construction phase. After 2040, these authors estimate an annual impact of 3979 to 4513 jobs to operate the plants. Simas and Pacca (2014) also separate the impact on construction and operational phases, both favorable to the municipalities that hold facilities.

Miskiewicz Miśkiewicz (2020) extends the indirect social benefits of renewable energies. The author found evidence that the reduction of CO_2 and SO_2 emissions lead to an improvement in the population's health, reflected in a decrease in the death rate. Andini et al. (2019) relate the construction of renewable energy facilities in Portugal with a sustainable improvement in macroeconomic rates. According to these authors, a one-time 1.10% increase in the growth rate of investment in renewable energy capacity generates a temporary positive effect on real GDP growth by 0.24% in the same quarter, which tends to disappear over time, being only 0.01% after five years. However, the authors estimated a reduction of 2.68% in the unemployment rate even after five years. Further, Swain and Karimu (2020) found evidence of a strong synergy between renewable energies and the United Nation's sustainable development goals in the European Union (EU).

The standard approach to estimating the economic impacts of energy development is the input–output modeling, which consists of regression-based econometric techniques concerned with identifying the statistical significance of a set of independent variables on a dependent variable (see, e. g., Simas and Pacca (2014); Rose et al. (2022); Faturay et al. (2020); Gonçalves et al. (2020); Miśkiewicz (2020); Andini et al. (2019); Arvanitopoulos and Agnolucci (2020)). Such an approach is well known in the literature and provides insightful results to guide policymakers. However, the modeling of an input–output problem may be troublesome. The analyst needs to assume an underlying production function that correctly relates the input and output variables, which may be challenging. In addition, just one response variable may be tested at a time.

In contrast, some authors use non-parametric approaches to measure the efficiency of renewable energy sources regarding some aspects. Tsaples and Papathanasiou (2021) provide a literature review on the use of Data Envelopment Analysis (DEA) to evaluate the efficiency of cities, countries, and regions in applying sustainability actions. DEA is also used to measure the efficiency of renewable facilities in a macroeconomic level. Menegaki (2013), for instance, applies DEA to assess the efficiency of 31 European countries regarding economic growth, measured through GDP and employment rate as output variables. The renewable energy sources were included as input variables in the model in terms of their percentage participation in each country's energy matrix.

Most of the non-parametric research applied to renewable energies is concerned with evaluating the efficiency of the compared units in a microeconomic dimension, such as a power plant level. San Cristóbal (2011) measures the efficiency of generic power plants using different renewable technologies and generation capacities. They use a multicriteria (DEA), more restricted than the original DEA formulation. By doing that, the author found just one full-efficient power plant that should meet all requirements the author considers important from a managerial perspective. Halkos and Tzeremes (2012) use a Bootstrap DEA to measure the efficiency of firms that operate in the Greek renewable energy market, a similar approach.

In contrast, Zeng et al. (2019) and Kolagar et al. (2020) evaluate macroeconomic dimensions regarding renewable energies. Nevertheless, they still evaluate the efficiency of comparable power plants level. Zeng et al. (2019) use a Data Envelopment Analysis to measure the efficiency of power plants in four dimensions: energy, economic, social, and environmental benefits. These authors comprise such dimensions in specific indexes by a fuzzy approach before processing the DEA analysis. Kolagar et al. (2020) use DEA and Fuzzy best-worst method (FBWM) in order to prioritize renewable energy sources in Iran.

As mentioned, this study contributes to the existing literature from a methodological perspective as we compare different renewable energy technologies in three dimensions (social, economic, and environmental) at a regional level.

Materials and Methods

The Brazilian regional and energy context

Brazil is the fifth largest country in the world by land area. In its 8.5 million km^2, there are 5,586 municipalities spread in 26 states and the Federal District, where live 215.5 million people (IBGE 2022). The World Bank accounted for a Gross Domestic Product (GDP) per capita in 2021 of 16,056 (measured in Purchasing Power Parities, PPP). As a matter of comparison, Argentina's GDP per capita was 23,627, China's was 19,338, and USA's was 69,287 in the same year (World Bank 2022b). As mentioned, the regional income distribution is very unequal in Brazil.

In this paper, we analyze the regional matter in terms of Brazilian mesoregions. Such regional division is defined by the Brazilian Institute of Geography and Statistics (BIGS, *Instituto Brasileiro de Geografia e Estatística* — IBGE), which groups municipalities by social-economic similarities (IBGE 2019). The Brazilian municipalities are divided into 137 mesoregions. Each one of them is unequal in terms of size and municipality quantity. The mesoregion "Sul/Sudoeste de Minas", in the State of Minas Gerais, for instance, has 146 municipalities, while the mesoregion "Norte do Amapá" has only five. Some mesoregions are large, with extensions as large as countries such as Portugal, Greece, and Austria. Despite extension disparities, Brazilian mesoregions are grouped by socioeconomic similarity. Then, this is a good aggregation unity for this study's purpose.

Energy generation is unequally spread in Brazil. All electricity plants in the country are interconnected in a centralized system. The Electricity System Operator (ESO - *Operador Nacional do Sistema*, ONS) decides which power plants should dispatch energy in a system that connects consumers and producers through transmission lines (Interconnected National System, INS — *Sistema Interligado Nacional*, SIN). According to ESO (ONS 2022c), the hydro, thermal, and wind plants prevail in this interconnected system. Table 1 shows the electricity generation installed capacity by source.

The Brazilian wind farms are concentrated in the northeast, south, and southeast, especially on the coast, where the wind speed is higher. Photovoltaic plants are highly concentrated in the country's northeast, while hydro plants are concentrated in the southeast (in quantity) and north (regarding installed capacity) (Gonçalves et al. 2020). On the other hand, the Brazilian population is highly concentrated in the southeast and southern regions. In the interconnected system, ESO defines the energy dispatch order considering a roll of criteria, which encompasses hydro reservoir capacity, electricity generation from intermittent sources (photovoltaic and wind), and regulatory issues, among others. The decision about the system's expansion, as well as which source of electricity should be prioritized, is shared among the Energy Research Office (ERO), ESO, and the Ministry of Energy. Each power plant interconnected in the system is previously projected in medium- and long-term plans designed by these agents.

From a historical perspective, we see that hydro potential has been explored in Brazil since the 1880s. However, just in the 1960s, the installed capacity increased consistently due to the creation of State Energy companies. The country hosts some of the largest hydro plants in the world, such as Itaipu (the second greatest, with 14 GW of capacity) and Belo Monte (the fourth greatest, with 11.2 GW of capacity). There are more than 150 hydro plants in Brazil and about 30 small hydro plants (ONS 2022a). Thermal plants are historically the complement to hydro plants in Brazil. The country's potential for alternative renewable energy (photovoltaic, biomass, and wind) has been explored on a commercial scale since the 2000s. In 2003, the Brazilian Government launched the Program for Incentives to Alternative Energy Sources (PROINFA), established in Law 10,438/2002. This program intends to increase the participation of alternative renewable energy sources in the electricity matrix, including incentives for small hydro plants and wind and biomass mills. Photovoltaic electricity is not included in PROINFA, but it has increased in late years. Brazil has approximately 130 photovoltaic facilities, and 750 wind farms (ONS 2022a). Furthermore, the system's expansion is being planned in terms of alternative renewable energy. For the upcoming 5 years, ESO projects to double the photovoltaic installed capacity and increase wind and thermal gas by one-third of their current installed capacity (ONS 2023).

Table 1 Electricity generation installed capacity in Brazil (2023)

Electricity generation source	Installed capacity in 2023 (MWh)	Share (%)
Hydro	109,348	58.4
Wind	25,246	13.7
Thermal (gas)	16,786	9.1
Biomass	15,409	8.4
Solar photovoltaic	8,079	4.4
Thermal (oil and diesel)	4,134	2.2
Thermal (coal)	3,017	1.6
Nuclear	1,990	1.1
Other	155	0.1
Total	184,200	100

Source: Electricity System Operator (ESO) ONS (2023)

Data envelopment analysis

Benchmarking models are techniques that compare different units in order to define relative efficiency measures among them. Such methods are centered on estimating the production frontier of a particular market, i.e., the set of inputs and outputs that produce the maximum possible quantity given a set of inputs. The production frontier estimation may use parametric and non-parametric techniques (Bogetoft 2013). Data Envelopment Analysis (DEA) is under the second group and uses linear programming to estimate the efficiency scores of comparable Decision-Making Units (DMUs). Charnes et al. (1978) define the DEA problem as follows: let the production set T be composed of sets $\mathbf{y} = [y_1, ..., y_s]$ having s output variables and $\mathbf{x} = [x_1, ..., x_m]$ having m input variables of n comparables DMUs, $DMU_i, i = 1, ..., n$. A linear programming problem is used to calculate the Farrell efficiency of the analyzed DMU_0. Equation 1 shows the output-oriented distance function regarding production set T. The output-oriented formulation is analogous to the original input-oriented model defined by Charnes, Cooper and Rhodes (Charnes et al. 1978). In this equation, the objective function equation denotes the Farrell Efficiency of DMU_0, $\phi_0 = \sum_{i=1}^{m} v_i x_{i0}$. The equation parameters u_r and v_i are the optimal weights associated with the outputs and inputs, respectively.

$$
\begin{aligned}
&\min \sum_{i=1}^{m} v_i x_{i0} \\
&\text{s. t.: } \sum_{i=1}^{m} v_i x_{ij} - \sum_{r=1}^{s} u_r y_{rj} \le 0, \quad j = 1, \dots, n \\
&\sum_{r=1}^{s} u_r y_{r0} = 1 \\
&u_r, v_i \ge 0
\end{aligned}
\tag{1}
$$

The linear problem 1 assumes a production set with *constant return to scale* (CRS). Under this premise, all units in the production set are compared. Further, the model calculates the efficiency measure assuming that all outputs are expanded at the same factor since they represent the radial distance from the frontier (Bogetoft and Otto 2010). Banker et al. (1984) introduced a less restrictive formulation, under the premise of a *variable returns to scale* (VRS) production set. In this last case, we still assume radial contraction of inputs, but we restrict the comparable units in the set by adding a constraint to the problem (see, e. g., Cook and Zhu (2008)). An output-oriented model with non-decreasing returns to scale (NDRS) is shown in Eq. 2. Variable φ allows restricted comparison among DMUs, granting the NDRS assumption.

$$
\begin{aligned}
&\min \sum_{i=1}^{m} v_i x_{i0} + \varphi \\
&\text{s. t.: } \sum_{i=1}^{m} v_i x_{ij} - \sum_{r=1}^{s} u_r y_{rj} + \varphi \le 0, \quad j = 1, \dots, n \\
&\sum_{r=1}^{s} u_r y_{r0} = 1 \\
&u_r, v_i \ge 0 \\
&\varphi \le 0
\end{aligned}
\tag{2}
$$

In this paper, we use an output-oriented DEA model. This premise means that the decision-makers should observe the output variables as the manageable variables in order to improve efficiency scores (Thanassoulis 2001; Bogetoft 2013; Bogetoft and Otto 2010; Cook and Zhu 2008). Likewise, this study assumes a Non-Decreasing Returns to Scale (NDRS) production set (also called Increasing Returns to Scale production set). This premise supposes that the proportional increase in outputs is larger than the underlying proportional increase in inputs (Hirschey 2009; Bogetoft and Otto 2010). Facilities with high fixed costs that may be spread with the rise in the production scale are frequently classified with NDRS production sets. The Brazilian energy regulator, for instance, assumes an NDRS production set for transmission electricity companies (Da Silva et al. 2019). Further, we evaluate the efficiency in terms of Shepard Distance Function, which is essentially the inverse of the Farrell ones, $\theta_0 = 1/\phi_0$ (Bogetoft and Otto 2010).

Model specification

In this study, we measure the efficiency scores of Brazilian regions where electricity generation facilities are installed. Efficiency refers to a three-dimension scenario regarding environmental and socio-economic indicators. This section details the model specification used to access such efficiency scores and the data used. The general problem formulation is depicted in Fig. 1.

Compared Units

The compared DMUs are the Brazilian mesoregions where electricity generation facilities are installed. We considered the electricity power plants in operation in Brazil in August 2021, according to ESO data (2022a). We took the facilities' annual energy generation capacity from the same dataset, measured in MWh. The precise location of each facility was extracted from the Brazilian Energy Regulator Agency information (ANEEL 2021). Operational data was calculated by power plant and then aggregated by municipality and mesoregion. The macroeconomic data was aggregated by municipality and mesoregion.

The analysis considers the power plants of renewable energy sources (photovoltaic, wind, and biomass), as well as small hydro plants (SHP). Thermic plants which use coal, gas, and nuclear power were also compared. The hydro plants were not included in the analysis because their installation and operation require specific studies, not extended to other facilities. Thermic plants that operate with diesel and oil were also discharged in the analysis since they represent a small portion of the electricity matrix and will be inactivated in the upcoming years (EPE 2021). The descriptive statistics of considered electricity plants are shown in Table 2.

As mentioned in section 1, we are interested in evaluating the regional effects of the energy facilities. So, we used the Brazilian mesoregions as units to compare. As mentioned, this regional division groups municipality by social-economic similarities. The analysis did not consider mesoregions without

Fig. 1 DEA model framework

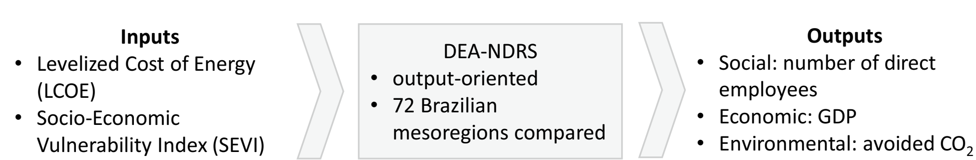


Table 2 Summary statistics of electricity plants by technology

Electricity plants	Descriptive Statistics					CO_2 Emissions			LCOE	Energy Production
Technology	Quant.	Installed Capacity (MWh)				gCO_2 eq/ kWh			R$/MWh (WACC 10%)	Capacity Factor
		Min	Med	Max	Std Dev	Min	Med	Max	Mean	
Wind (onshore)	753	3.0	28.4	105.0	10.6	7	11	56	143.8	0.3
Solar (onshore)	131	2.0 3	30.0	95.3	11.5	18	48	180	170.5	0.3
Small hydro plants (PCH)	33	10.0	26.1	31.4	7.4	1	24	2200	225.3	0.3
Nuclear	2	640.0	995.0	1,350,0	502.0	3.7	12	110	498.7	0.8
Biomass	66	4.0	50.0	409.3	56.9	130	230	420	279.1	0.3
Biomass (residuals)	15	43.5	181.2	466.2	114.0	130	230	420	279.1	0.3
Biomass (industrial residuals)	11	30.0	226.0	490.0	119.6	130	230	420	279.1	0.3
Coal	8	232.0	355.1	720.3	148.5	740	820	910	401.4	0.8
Gas (simple cicle)	38	25.0	225.7	1,593.2	296.9	410	490	650	564.5	0.3

Source: ESO (2022a) for power plant descriptive statistics, IPPC, Bruckner et al. (2014) for CO_2 emissions and EPE (2021) for LCOE and Capacity Factor

any of the mentioned energy facilities. We aggregated data in mesoregions where there is more than one energy facility. A total of 71 mesoregions were compared in the DEA analysis. The list of mesoregions and their electricity generation installed capacity is provided in Table 3 of Appendix A.

Input variables

In a production set analysis, a common approach is to measure the efficiency considering the capital expenditure in the system, as we may observe in classical economic theory handbooks (see, e.g., Blanchard (Blanchard 2018)). In these terms, a facility's Capital Expenditure (CAPEX) and the Operational Costs to operate it (OPEX) could be good proxies of the capital available in the facility region. Therefore, we used the Levelized Cost of Energy (LCOE) as the input variable. Andres et al. (De Andres et al. 2017) ddefine the LCOE calculation as the sum of total CAPEX, OPEX, and decommissioning costs, discounted to present-day value, divided by the electricity supplied to the grid throughout the operational life of the technology.

We choose to use the LCOE values calculated by ERO (2021), which uses the LCOE approach proposed by the American National Renewable Energy Laboratory (NREL (1995)), generically shown in Eq. 3. In addition, ERO (2021) estimates the LCOE values for different energy sources using sector no-public data, making these estimates the most complete available information.

$$LCOE = \frac{FCR \times TCC + FOC}{AEP} + VOC \tag{3}$$

In this generic equation, *FCR* refers to the Fixed Charge Rate, *TCC* corresponds to the Total Capital Costs or CAPEX (in monetary units), and *FOC* is the Fixed annual Operating Cost (also in monetary units). *AEP* refers to the Annual Electricity production (in kWh), and *VOC* is the Variable Operating Cost (in monetary units per kWh). ERO (2021) uses a 10-year dataset (from 2010 to 2021) for OPEX, CAPEX, and VOC corrected by the Brazilian inflation index to the basis date of December 2021. Such data were registered by companies that run (and won) electricity procurement auctions. We used in this study the LCOE values calculated considering the discount rate of a Weighted Average Cost of Capital (WACC) of 10% per year. Finally, it is worth mentioning that the ERO (2021) estimates for the LCOE are in Brazilian Reais per MWh (R$/MWh). The considered LCOE values by technology are shown in Table 2.

For DEA modeling, the LCOE (in R$/MWh) of each power plant was multiplied by each facility's installed capacity, in MWh. We also applied a capacity factor in the estimated energy production, according to ERO numbers (EPE 2021). This factor considers the proportion of operation time of a power plant. We summed up the resulting LCOE in Brazilian Reais (R$) in each mesoregion, consolidating one input variable. Equation 4 summarizes the calculation of the aggregated LCOE variable to each mesoregion *i*: the sum of the installed capacity of each *j* electricity facility of technology *k*, multiplied by the technology LCOE and Capacity Factor (CF).

$$LCOE_i = \sum_{j=1}^{n} \left[Capacity_{jk} \times LCOE_k \times CF_k \right] \tag{4}$$

Inequality in Brazil is a relevant issue. A mesoregion efficiency in operating a number of power plants may be affected by factors regarding labor qualification, violence, etc. Thus, we included a "non-monetary cost", which is related with the social vulnerability in the region. We used the Socio-Economic Vulnerability Index (SEVI, Indicador de Nível Socioeconômico, INSE) (MEC 2023). The Brazilian Ministry of Education calculates annually this index, by applying an extensive questionnaire to last-year primary education students. The index is summarized by city as an average scale from less to more socioeconomic vulnerable. Therefore, we aggregated the inverse of such an index in the mesoregions regarding the average weighted by the population size. In our new modeling, the socioeconomic vulnerability may be considered an "extra cost" to an efficient performance of an enterprise in generating socio-economic development: the higher the observed population vulnerability, the higher the challenge in developing growth.

Output variables

The DEA output variables were selected to represent the three dimensions of the efficiency measure we want to analyze: social, economic, and environmental. The social impact is measured by the number of direct employees the electricity sector generates in the mesoregion. We used data from the Brazilian Ministry of Labor (MTE 2022): the official General Register of Employed and Unemployed shows the number of employed people by city, considering the employer's economic activity. We selected the economic activities related to **electricity generation**, **electricity transmission**, and **electricity distribution**. In this analysis, we did not include indirect jobs into account.

The economic dimension is analyzed through each mesoregion's total Gross Domestic Product (GDP). We used data from BIGS (IBGE 2019) regarding the year 2019. The third dimension analyzed in the efficiency scores is the environmental, measured through carbon emissions. We considered the carbon emissions in a life cycle approach to each electricity generation technology, i.e., the expected emissions from the construction process until operation and facility decommissioning. This approach is preferable to analyze the carbon emissions regarding the plant operation. This is because the emissions during the implementation process of renewable sources facilities may be significant. We used data from the third Annex of the report from the Intergovernmental Panel on Climate Change (IPCC) (Bruckner et al. 2014).

The DEA modeling implies that the output variables are desirable, and their increase will make the DMUs more efficient. Clearly, this is not the case with the CO_2 emissions that we want to reduce to improve environmental efficiency. Therefore, we adapted the CO_2 emissions variable to reflect this intention: the avoided equivalent CO_2 emissions variable comprises the difference from the technology's emission to the worst case (the emissions from the coal plants).

Results and discussion

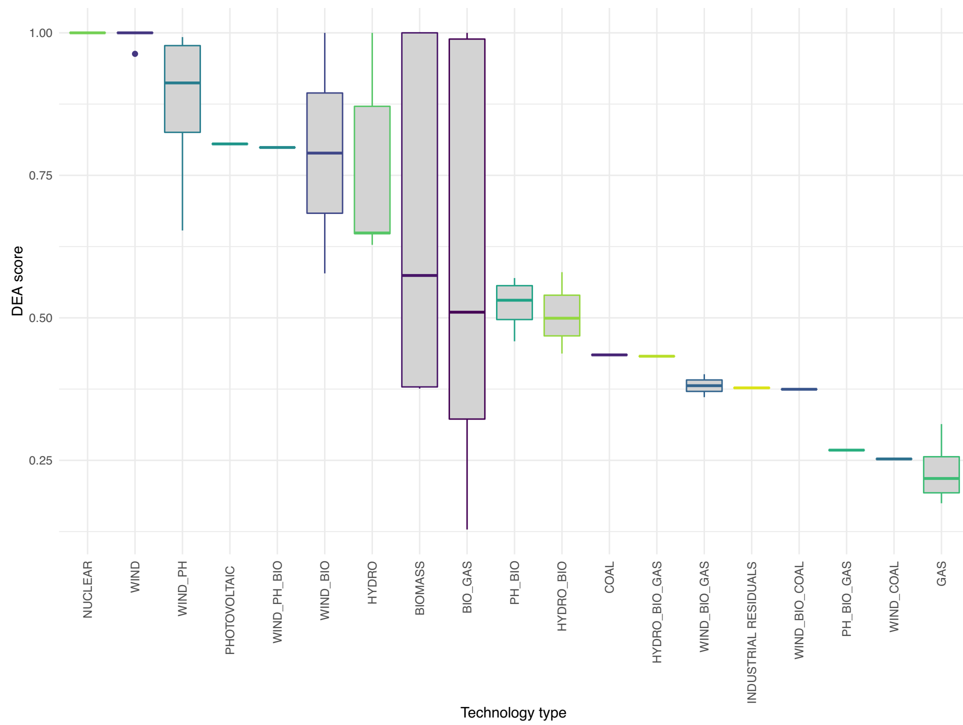
We estimated the efficiency frontier assuming an output-oriented distance function (Eq. 2) using the R package *Benchmarking* (Bogetoft and Otto 2022). The underlying premise is that the decision-maker must increase the model outputs in order to improve its efficiency score. This assumption holds in this case, considering the model inputs nature (Fig. 1): the decision-maker cannot manage the vulnerability index, and LCOE is considered constant for every technology. Thus, social, economic, and environmental benefits are the manageable variables. As we used a Shephard output distance function, full-efficient mesoregions reached a score of 1.0, and non-efficient mesoregions performed above 1.0, up to 0.0.

The mesoregions DEA scores reached a mean of 0.6801. The 71 efficiency scores ranged from 0.1287 to 1.000, and 20 of them were full-efficient ($\theta_i = 1.00$). Mesoregions that hold nuclear, wind, and photovoltaic facilities are consistently more efficient on the three-dimensional analysis than mesoregions where thermal power plants are installed. The mean efficiency score of mesoregions that hold wind facilities is 0.9969, while the mean efficiency of mesoregions where there are photovoltaic power plants is 0.8051. Regions that hold both technology types have an average efficiency of 0.8792. Figure 2 shows the boxplots of the efficiency scores of mesoregions grouped by electricity technology. Some mesoregions hold more than one type of electricity generation technology. In those cases, the mesoregions are grouped by the combination of generation sources.

Mesoregions where biomass power plants are located reached very unequal efficiency scores: the average efficiency is 0.6543, ranging between 0.3759 and 1.00. Regions that hold biomass power plants and thermal gas facilities are, on average, 0.5927 efficient, while areas with biomass and wind facilities perform on average 0.5226. The high amplitude in these efficiency scores suggests a low pattern in the socio-economic benefits due to biomass power plants. Biomass facilities may operate with various raw materials and very distinct installed capacities, which could explain the high efficiency dispersion.

Mesoregions with the worst efficiency scores are those where gas power plants are installed ($\theta = 0.2312$, on average). The combination of gas facilities and renewable electricity sources diminishes this effect. High CO_2 emissions explain these scores. Even socio-economic benefits cannot overcome the comparatively low performance of this electricity source in this indicator. It is interesting noticing that the only region that holds just coal facilities reach 0.4350 efficiency score, close to the sample mean. That is the mesoregions with gas power plants worst perform in the ranking than those with coal thermal.

Fig. 2 Efficiency scores by technology type. Technology code: Photovoltaic (PH), Wind (WIND), Biomass (BIO), Small Hydro plants (HYDRO), Nuclear (NUCLEAR), Thermal Gas (GAS), Thermal coal (COAL)



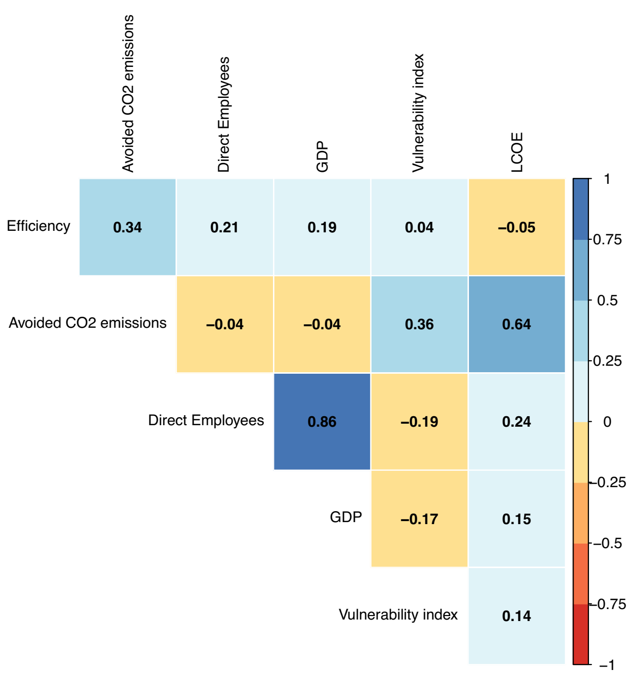


Fig. 3 Correlation matrix of DEA scores and model variables

The factors which influence the efficiency scores may be evaluated in terms of the correlation coefficient of the index and the model variables: the higher the correlation, the greater the variable influence in the efficiency assessment. Figure 3 shows the correlation matrix of DEA scores and the model variables. In this figure, darker blue colors represent Pearson correlation coefficients closer to 1.00 (strong positive correlation), while darker red colors represent correlation coefficients closer to −1.00, indicating a strong negative correlation. In the first line of the matrix, we may see the correlation coefficient between the efficiency scores and the variables Avoided CO_2 emissions (+0.34), Direct employees (+0.21), GDP (+0.19), Vulnerability index (+0.04), and LCOE (−0.05). The positive correlation between scores and the output variables implies that all of them were considered in the DEA efficiency assessment. Regarding this criterion, the environmental dimension is the most important, and direct employment is the second most crucial variable in differentiating mesoregions' efficiency.

It is interesting to notice that some variables are highly correlated, such as Direct Employees and GDP (0.86). However, differently of regression-based analysis, for DEA modeling, the correlation among variables is not a significant problem. The compared units will access the efficiency frontier due to one variable or the other without multicollinearity issues.

Finally, Fig. 4 shows the efficiency scores of each mesoregion and the location of power plants. Darker green colors represent efficiency scores closer to 1.0 and light green colors represent efficiency scores closer to zero. Mesoregions in white color were not included in the analysis, because they do not comprise any considered generation power plant. This figure helps to understand the dispersion of efficiency scores according to the generation technology,

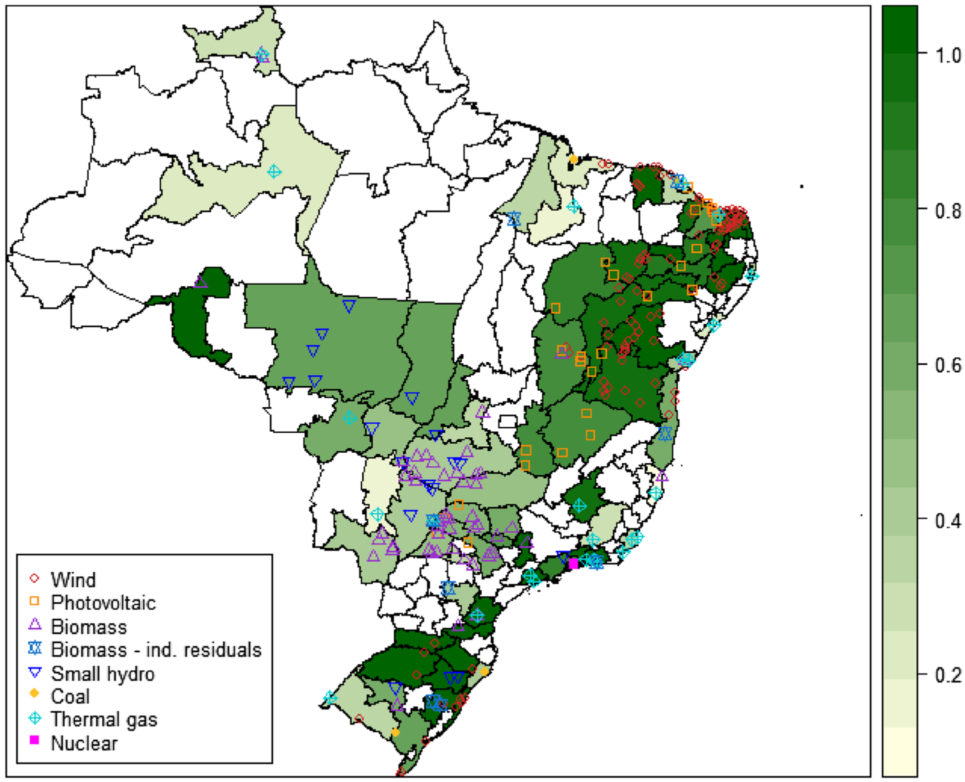


Fig. 4 Efficiency scores by mesoregion and electricity generation facilities

described before. Also, Fig. 3 raises a hypothesis regarding the correlation between the efficiency scores and the concentration of power plants in a mesoregion. Except for mesoregion Madeira-Guaporé, located in the North region in the state of Rondônia, which is full efficient and holds just one biomass power plant, most full efficient mesoregions comprise more than one electricity generation facility. DEA analysis considered the absolute number of power plants' total installed capacity, but a synergy considering close facilities may influence the efficiency scores.

Results corroborate the findings of ̧regarding the positive influence of wind power plants in Brazil. Moreover, we extend their conclusion when we compare wind facilities' socioeconomic and environmental impact to other electricity generation technologies and show that wind and solar are more efficient in these aspects than other sources. Further, one interesting discussion that the results raise refers to the efficiency scores of coal and gas power plants. Carbon emissions from coal facilities are higher than the carbon emissions of gas thermal power plants. But, even then, the efficiency scores of mesoregions with just gas facilities are worse than the efficiency score of the mesoregion that holds just a coal power plant. The mesoregion Sul Catarinense holds one coal facility and reaches a 0.4350 efficiency score, 20 percentage points above the average score of mesoregions that hold just gas power plants. We may infer that this mesoregion is comparatively more efficient than peers in other output (GDP and direct employment).

Authors that used parametric models also found a positive relation between renewable electricity facilities and job generation (Arvanitopoulos and Agnolucci 2020; Frondel et al. 2010; Rose et al. 2022). The results confirm those conclusions and add a comparative component in the analysis regarding different electricity sources once DEA provides relative efficiency scores.

An interesting discussion topic refers to the thermal biomass scores. Results show a dispersed and unequal efficiency from biomass facilities, probably due to the high variable raw materials and installed capacities. Authors as Yaqoob et al. (2022); Teoh et al. (2022) sow that different technologies in biofuels affect the carbon emissions. Although the micro evaluation of the quality and adequacy of biofuels is not the center of this analysis, such a topic is relevant to policymakers and must be observed.

Concluding remarks

Renewable electricity generation power plants are frequently associated with good impacts on carbon emission mitigation and job generation. In this sense, we sought to answer if there is a difference in the efficiency of electricity generation technologies' capacity to induce regional socioeconomic and environmental development. To do that, we measured the relative efficiency scores of Brazilian mesoregions that hold power plants regarding environmental and socio-economic dimensions. Besides, a non-parametric efficiency frontier method was applied to generate efficiency scores. Results show that the efficiency scores are highly dispersed and may be grouped according to the electricity source present in the evaluated mesoregion. The mesoregions that contain nuclear, wind, and photovoltaic power plants (or a combination of these technologies) perform better than mesoregions that comprise biomass, gas, and coal thermal facilities. In addition, the results show that renewable energy facilities perform better than non-renewable facilities in direct job generation and GDP aggregation. Regarding non-renewable energy, mesoregions with coal power plants are more efficient than gas thermal plants in the direct jobs dimension.

The necessity of expanding the electricity generation capacity in Brazil needs to be coherent with the country's goals for carbon emissions. The expansion of renewable energy sources is a safe path in that sense, which also contributes to the socio-economic regional development. It is worth mentioning that the expansion of thermal gas capacity planned for the next five years (ONS 2023) in Brazil clashes with sustainable goals and planning. Our findings show that such facilities are not efficient in any of the three analyzed dimensions.

Our study is not exempt from limitations. For future research, we consider a review of the model output variables and a second-stage procedure that relates the efficiency scores with contextual variables. This last application may improve the identification of causations of efficiency.

Appendix A: Brazilian mesoregions

List of Brazilian mesoregions considered in the analysis. See Table 3.

Table 3 Summary statistics of Brazilian mesoregions

Mesoregion name	Region	Electricity generation Installed Capacity (MWh)								GDP
		Wind	Gas	Photovoltaic	Biomass	Coal	Nuclear	SHP	Total	
Norte Fluminense	Southest		2,362		757				3,119	81,923
Metropolitana RJ	Southest		1,868		851				2,719	1,000,327
Sudeste Piauiense	Northeast	2,234		396					2,630	7,001
Centro Norte Baiano	Northeast	2,618							2,618	36,746
Norte Cearense	Northeast	1,018			218				2,321	22,868
Agreste Potiguar	Northeast	2,117							2,117	5,793
Centro Sul Baiano	Northeast	1,618		415					2,043	32,554
Sul Fluminense	Southeast						1,990		1,990	45,845
V. S. Francisc. Bahia	Northeast	1,498		391					1,989	15,944
Oeste Potiguar	Northeast	1,412	323	175					1,910	17,848
Central Potiguar	Northeast	1,878							1,878	8,382
Sudeste Riograndense	South	952				695			1,647	30,827
Leste Sergipano	Northeast		1,593						1,593	32,047
Centro Maranhense	Northeast		1,247		181				1,428	12,231
Centro Amazonense	North		1,411						1,411	98,956
Leste do MS	Midwest		235		979			60	1,275	58,381
Leste Potiguar	Northeast	1,113							1,113	38,752
Sul Goiano	Midwest				930			91	1,021	52,526
Metropolitana de SP	Southeast		791		190				981	2,081,362
Metropolitana de POA	South	599			369				968	226,455
Jaguaribe	Northeast	735		134					869	8,714
Sul Catarinense	South					857			857	35,471
Sudoeste Riograndense	South	162	375		265				802	23,784
Norte Maranhense	Northeast	426				360			786	45,245
Bauru	Southeast			150	626				776	55,896
Sudoeste Piauiense	Northeast	58		705					763	9,566
Noroeste Cearense	Northeast	762							762	17,747
Sudoeste de MS	Midwest				651				651	35,532

Table 3 (continued)

Mesoregion name	Region	Electricity generation Installed Capacity (MWh)								GDP
		Wind	Gas	Photovoltaic	Biomass	Coal	Nuclear	SHP	Total	
Aracatuba	Southeast			204	431				634	22,790
Agreste Pernambucano	Northeast	539							539	32,648
Metropolitana Recife	Northeast		325		208				533	1,12,622
Centro-Sul MT	Midwest		335		194				529	62,616
Metropolitana Curitiba	South		315		181				496	230,230
Presidente Prudente	Southeast			81	390				471	23,537
Centro Oriental PR	South				465				465	33,561
Norte de Minas	Southeast			442					442	27,700
Extremo Oeste Baiano	Northeast	66		340	30				436	21,564
Metropolitana Fortaleza	Northeast		216	81	111				408	93,417
Borborema	Northeast	378							378	3,459
Sertao Pernambucano	Northeast	138		163					301	12,027
Sao Jose do Rio Preto	Southeast			145	152				297	56,120
Norte Mato-grossense	Midwest							265	265	52,625
Metropolitana Salvador	Northeast	30	214		17				260	130,930
Oeste Maranhense	Northeast				255				255	19,996
Litoral Norte ES	Southeast		204		33				237	18,653
Metropolitana de BH	Southeast		151		84				235	263,924
Noroeste de Minas	Southeast			213					213	10,956
Sertão Paraibano	Northeast	94		108					202	10,917
Sul Baiano	Northeast	71			127				197	35,378
S. Franc. Pernambucano	Northeast	179		10					189	3,466
Norte de Roraima	North		97		84				181	33,409
Centro Norte de MS	Midwest		177						177	38,406
Assis	Southeast				174				174	12,832
Sudeste Mato-grossense	Midwest				73			86	159	25,060
Triangulo Mineiro	Southeast				152				152	92,991
Madeira-Guapore	North				145				145	39,956
Oeste Catarinense	South	129							129	53,151
Nordeste Rio-grandense	South							103	103	54,035
Serrana	South	93							93	14,813
Zona da Mata	Southeast		87						87	51,694
Ribeirao Preto	Southeast				70				70	10,2657
Campinas	Southeast				70				70	250,419
Centro Goiano	Midwest				68				68	26,204
Vale do Paraiba Paulista	Southeast							60	60	118,200
Noroeste Rio-grandense	South	55							55	86,780
Centro Ocidental RS	South				8			31	39	18,159
Noroeste Goiano	Midwest							30	30	5,891
Nordeste Mato-grossense	Midwest							29	29	12,042
Sul Cearense	Northeast	23							23	5,603
Araraquara	Southeast				5				5	34,078
Norte Catarinense	South				4				4	72,564

Source: ESO (2022a) and BIGS (IBGE 2019)

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