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Dynamic Data Envelopment Analysis Model Involving Undesirable Outputs in the Electricity Power Generation Sector: The Case of Latin America and the Caribbean Countries

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Abstract: Studying the evolution of the efficiency of the electricity generation sector is a relevant task for policy makers, and requires the undesirable outputs derived from the activity to be considered in the evaluation. In this work, we propose a dynamic slack-based Data Envelopment Analysis (DEA) model that incorporates the assumption of weak disposability between the generation of electricity from fossil sources and the CO_2 emissions caused by the sector to measure the technical efficiency of 24 Latin American and Caribbean countries in the period 2000–2016. The results show that, of the total number of countries studied, four are efficient overall, and four groupings of countries in relation to the levels of efficiency achieved are also identified. These results are important given that less-efficient countries can, through learning, increase their efficiency in electricity generation or emulate the future strategies proposed by the most efficient countries.

Keywords: dynamic DEA; efficiency measurement; electricity power generation; weak disposability; undesirable outputs

1. Introduction

Measuring the efficiency of production systems is an important task in economic science, and different studies have addressed this problem with different methodologies. In regulated sectors, such as the electricity sector, the evaluation of productive efficiency has been promoted. Particularly, in the activity of electricity power generation, this stimulus is created by the dependence that exists on the traditional sources of generation, such as fossil sources, considering their impact on the environment caused by emissions of greenhouse gases (GHG) [1].

Electricity generation in the Latin American region has been largely composed of two types of sources: hydroelectric and fossil energy. In 2017, these two sources made up almost 88% of the total generation, at 47.52% and 40.25%, respectively. There has been an important change in the use of different types of energy compared to 1990—a time when there was almost total dependence on generation by these two sources, at 95.76% of the total, and there was also a greater relative importance of hydroelectric energy, which made up 65.69% of total energy compared to 33.43% of fossil sources [2].

Currently, developed and developing countries are concerned about increasing the proportion of renewable sources within their energy matrixes, which has resulted from essential decisions to address climate change [3]. This is supported by the fact that the electricity generation sector is the most important for CO_2 emissions, followed by the transport sector and the industrial sector [4], although the use of renewable energy in Latin America and the Caribbean was lower in 2018, at 27.59% of the total, compared with its usage proportion in the rest of the world, at 41.93% [5]. To this extent, the comparison of the efficiency of electricity generation activity is a relevant task for policy makers, particularly considering the emissions caused by generation activity.

The aim of this research is to evaluate the evolution of the technical efficiency of the electricity generation sector of 24 countries in Latin America and the Caribbean during the period 2000–2016, with a dynamic slack-based DEA model from an output-oriented perspective. The proposed model considers a desirable output, an undesirable output and three inputs, of which two aim to capture the temporal interdependence in the generation activity, which are called link variables. In our model, the desirable output is the generation of electricity, while the undesirable output is the total CO_2 emissions derived from the generation of electricity. Although Sánchez et al. [6] studied the evolution of the efficiency of electricity generation in Latin American countries between 2006 and 2013, they did not consider the possible temporal interdependence present in the activity, nor did they use the installed capacity in the different generation sources as inputs or assume a weak disposability between generation and CO_2 emissions.

The contribution of this research is twofold at the country level: (1) it is the first study to incorporate the dynamic component of the DEA methodology, capturing the possible temporary interdependencies that exist in the generation activity when seen as a production system; and (2) it is the first investigation to capture the assumption of weak disposability between fossil generation sources and CO_2 emissions, which affects the efficiency measures calculated by the DEA models.

The rest of the document is organized as follows. Section 2 presents the main studies related to the DEA methodology as applied to the electricity sector. Section 3 presents the methodology, which introduces the concepts that are used to capture the environmental and dynamic components, and the methodology of DEA assessment by a non-radial model is also given. Section 4 shows the descriptive statistics of the variables used in the evaluation; it also describes the electricity generation sector and presents the results of the calculated efficiency levels for the 24 countries based on the proposed dynamic DEA model. Section 5 presents the conclusions, discussions and limitations of the study.

2. Literature Review

Recently, Data Envelopment Analysis (DEA) has become one of the main tools for environmental assessment. This methodology was initially proposed by Charnes et al. [7], and since then it has become an important tool for measuring relative efficiency in different fields [8]. This tool can serve as a guideline for firms and policy makers. Since Faere et al. [9] introduced the concept of the undesirable output, the use of DEA has widely spread in environmental assessment, becoming the most popular application area within the DEA methodology [10]. This section presents a complete review of this methodology and its application in the power generation sector, and its different variations in terms of environmental models and dynamic models.

2.1. DEA in Power Generation

Several studies have implemented the DEA methodology to assess the efficiency of the electricity generation sector at the generation firm level and at the geographical level.

Some works at the firm level include that of Golany et al. [11], which measured the efficiency of power plants in Israel; the works of Shermeh et al. [12] and Khalili-Damghani et al. [13], which investigated Iran regional power companies; the work of Yang and Pollit [14] regarding Chinese coal-fired power plants; the work of Sueyoshi and Goto [15] regarding U.S. coal-fired power plants; and the work of Cherchye et al. [16], which explored U.S. fossil and non-fossil plants. The last four studies also included an environmental assessment, including the emission of polluting gases as an undesirable output.

At the geographical level, Chang and Yang [17] measured the efficiency of the power generation of municipalities in Taiwan, while Tao and Zhang [18] investigated 16 Chinese cities located in the Yangtze River Delta. These studies introduced environmental analysis considering different pollutants of the air and water. Other works have focused on conducting electricity generation performance assessment, and they have taken countries as decision-making units; among the researchers in this area are Dogan and Tugcu [19], who evaluated the efficiency of the G-20 group; Whiteman [20] and Yunos and Hawdon [21], who investigated 95 and 27 countries of the world, respectively; Bi et al. [22] who considered 26 OECD member countries; Zhou et al. [23], who used information from 126 countries around the world; Li et al. [24] who performed an analysis for the G-20 group; and Sánchez et al. [6], who measured the efficiency of Latin American countries. These four last groups performed efficiency evaluations that considered the undesirable outputs and external costs of the activity.

2.2. Environmental DEA

Policy makers must consider environmental efficiency assessment at a country level in order to regulate to promote environmental protection and economic development. In this way, some studies have involved undesirable outputs in the definition of DEA. The treatment of these undesirable outputs within the DEA literature has been presented in three ways, according to Dyson et al. [25]: (1) inverting the anti-isotonic factor, (2) subtracting the value of the undesirable factor from a large number or (3) treating the undesirable output as an input. We have opted for the third strategy.

The DEA model for environmental assessment requires the incorporation of different production factors (desirable outputs, undesirable outputs and inputs), and this requires all variables to be greater than or equal to zero. Here, non-radial models satisfy this requirement; therefore, they can measure the efficiency of DMUs (decision-making units) that contain negative or zero values in any of their inputs or outputs.

Conventional energy efficiency measures that do not consider undesirable outputs are biased because firms can lose their productive efficiency due to a negative output [26]. Following Faere et al. [9], when evaluating the performance of producers, it makes sense to compensate for the supply of desirable outputs, as well as to penalize the provision of undesirable outputs. In other words, "positive" and "negative" factors should be treated asymmetrically when measuring a producer's performance. The performance measures outlined above, in fact, treat positive and negative factors asymmetrically, valuing the former and ignoring the latter. This extreme form of asymmetry characterizes much of the literature on measuring productivity and efficiency, so it is necessary to introduce concepts that allow the smoothing of this approach.

Unlike traditional DEA models, the model proposed by Faere et al. [9] assumes that the reduction of undesirable outputs is costly in terms of desirable outputs. To reduce undesirable outputs, part of the production of desirable outputs must be sacrificed. In the literature, this implies moving from the assumption that the technology of undesirable outputs is "freely (or strongly) disposable", where the variation of undesirable outputs does not represent any cost in terms of production, to the assumption of "weakly disposable" outputs, where such variation involves a cost, given the conceptual incorporation that implies that desirable and undesirable outputs are jointly produced. In this work, the desirable outputs $\left(y^d \epsilon\, R_+\right)$ are distinguished from the undesirable outputs $(y^u \epsilon\, R_+)$ and the inputs are denoted by $x \,\epsilon\, R_+$.

According to Faere et al. [9], mathematically, the concept of strong disposability between desirable and undesirable outputs can be expressed as follows:

$$\left(y^u, y^d\right) \in P(x) \;\rightarrow\; \left(y^d - s\right) \in P(x),\; s \geq 0 \tag{1}$$

Given a vector of inputs (x) and a production possibility frontier $P(x)$, if a level y^d can be reached, then $y^d - s$ can also be produced for any $s \geq 0$.

On the other hand, it is common that certain bad outputs cannot be separated from the corresponding good outputs; therefore, to reduce a bad output, it is necessary to reduce the good output [27]. Within the DEA literature, this is the concept of weak disposability, and it can be denoted as follows:

$$\left(y^u, y^d\right) \in P(x) \ \rightarrow \ \left(\theta y^u,\ \theta y^d\right) \ \in P(x), \text{ with } 0 \leq \theta \leq 1. \tag{2}$$

Given a vector of inputs (x) and a production possibility frontier $P(x)$, on the one hand, a total decrease of the undesirable output $(y^u = 0)$ is not possible unless the desirable output is also zero $\left(y^d = 0\right)$; on the other hand, it can only be decreased proportionally $\left(y^u,\ y^d\right)$ when $0 \leq \theta \leq 1$. In this case, y^u and y^d are called non-separable undesirable outputs and non-separable desirable outputs, respectively. We consider that the weak disposability assumption in the activity generation activity is necessary considering that it is not possible to generate electricity using fossil fuels without incurring CO_2 emissions.

2.3. Dynamic DEA

Traditional DEA models do not consider the interdependencies between consecutive periods. This can be a problem in the case of electricity generation because the level of installed capacity available for a country is determined by the installed capacity in the immediately preceding period, which modifies the efficiency assessment [28]. Static DEA models assume that the inputs in period t are mixed with the technology of period t to produce the outputs of period t.

Färe and Grosskopf [29] were the first to incorporate variables that connect consecutive periods, called link flows, from carry-over equations into the DEA approach, allowing inputs to be stored by modeling "savings" in period t to be used in period $t + 1$. Later, Tone and Tsutsui [30] identified different kinds of carry-over activities and proposed a dynamic slack-based model.

3. Materials and Methods

This section first presents the description of the data and the source of information; subsequently, the definition of the variables that are part of the proposed model is presented; and finally, the strategy used to measure the efficiency of the electricity generation of the countries of Latin America and the Caribbean is shown.

3.1. Data and Sources

The data set used corresponded to annual data between 2000 and 2017 from 24 countries in Latin America and the Caribbean. The data collected originated from two sources: The U.S. Energy Information Administration (EIA) and the International Energy Agency (IEA). We collected the CO_2 emissions from the generation of electricity from the IEA, while GDP, installed capacity and generation of electricity were collected from the EIA.

3.2. Definition of the Variables

The proposed model includes a desirable output, an undesirable output, three inputs and two link variables, which are described below.

- Desirable output

As a desirable output, we used the generation of electricity, measured in TWh, distinguishing whether the generation sources were based on fossil sources—oil, gas and coal—or non-fossil sources—nuclear, geothermal, solar, wind, biomass and waves—to capture the assumption of weak disposability between CO_2 emissions and electricity generation through fossil sources. This strategy was used by Cherchye et al. [16] and Walheer [31] to isolate the emissions of three polluting gases, but the latter used electricity generation as a necessary input to produce CO_2 emissions and GDP.

- Undesirable output

To capture the dependence between the generation of electricity based on fossil sources and the CO_2 emissions that they incur, we discriminated between energy from clean generation sources and energy generated from fossil fuels. This strategy allowed us to capture the proportional variations between the non-separable desirable output—fossil-generation—and the CO_2 emissions, known in the DEA literature as the assumption of weak disposability and introduced by Faere et al. [9].

As an undesirable output, we used the CO_2 emissions generated by the electricity generation activity, measured in MTm. Due to the availability of information, we used observed data for 2016 and 2017, while we estimated the data for the period 2000–2015 from the CO_2 emissions from electricity and heat production in each country in 2016 and the electricity generated from fossil sources in the same year. For Guyana, we created an estimate for the entire period using the regression from other countries because of the lack of information regarding CO_2 emissions from electricity and heat production for this country. We think that this measure represented a good proxy for CO_2 emissions generated by the electricity sector considering the high R-square of the regression of 0.9886.

- Inputs

We incorporated three inputs: the gross domestic product (GDP) per capita, the installed capacity of non-fossil generation sources and the installed capacity of fossil generation sources. These last two variables were also used to capture the inter-temporal dependence of electricity generation, entering the model as link variables.

The GDP of each country has been used in different studies within the DEA methodology as a desirable output [22,32–35]. We believe that, within the productive process presented by each DMU, one of the main inputs is the GDP per capita, in the sense that high-income countries can benefit from greater technological innovation and make greater efforts in R&D to improve energy efficiency [36]. This decision to use GDP per capita as an input was also based on studies that have evaluated the causality between electricity generation and economic growth, finding a unidirectional relationship for economic growth and electricity generation [37–39]. This indicator was measured in billions $2015 PPP. In addition, Dyson et al. [25] recommended the use of type of variables to control the lack of homogeneity in the units tested.

The installed capacity has been used in different studies as an input for electricity generation. For example, Yunos and Hawdon [21] and Li et al. [24] used the installed capacity of fossil sources as an input without taking into account the different non-fossil sources of generation. In addition, Whiteman [20], Chen et al. [36] and Dogan and Tugcu [19] used the installed capacity of non-fossil sources in a disaggregated manner. This variable is measured in GW.

- Link variables

In this research, we considered that there is a dynamic component within the electricity generation sector that depends on the installed capacity for the different generation sources. The main reasons for this is as follows: (1) the level of installed capacity available for each country in year t is determined by the installed capacity level in the immediately preceding term, $t-1$ [28]; (2) it can be assumed that the installed capacity in each country is a quasi-fixed input, and because of the large investment that this entails, it makes it difficult to adjust this to optimum levels every year [40]; and (3) the level of installed capacity in a year t has impacts on the generation in year $t+1$, taking into account the fact that this input also functions as a warehouse, either for electricity, through batteries, or of potential generation—for example, the electricity power output that depends on the water flow in the penstock and the water accumulated in the reservoir [41].

3.3. Model Approach

To measure the efficiency of electricity generation in the 24 countries mentioned, we propose a dynamic slack-based DEA model and assume a constant return to scale (CRS). The model is based on the dynamic slack-based DEA model proposed by Tone and Tsutsui [30], which has been expanded to include undesirable outputs and to capture the assumption of weak disposability between the generation of electricity from fossil sources and emissions of CO_2, presented in Tone [42].

The model structure is represented in Figure 1. We observe n countries over T terms. At each term t, each country uses its respective inputs (GDP, non-fossil-fuel installed capacity and fossil-fuel installed capacity) to produce the desirable output (non-fossil and fossil electricity generation). A variation in fossil generation implies a proportional variation of the undesirable output (CO_2). The link variables connect consecutive terms ($1, \ldots, t-1, t, t+1, \ldots, T$); in our model, the level of installed capacity available for each country in term t determines the installed capacity in the immediately succeeding term, $t+1$, and is determined by the installed capacity in the immediately preceding term, $t-1$.

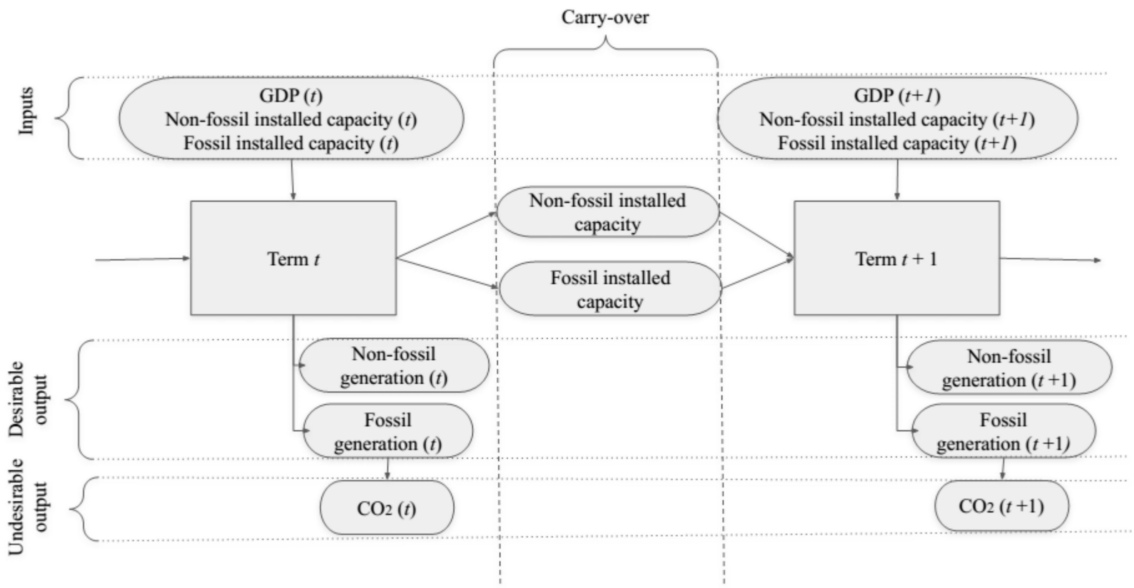


Figure 1. Model structure.

The dynamic DEA model defines a production possibility set for each term based on the observed output and input values of the DMUs in each term t.

Following Zhou and Liu [43], the maximization of the desirable output and minimization of the undesirable output can be reached with an additive DEA model with the next objective function:

$$\max SDO\_NF_{ot} + SDO\_F_{ot} + SUO\_CO2_{ot}. \tag{3}$$

However, continuing to follow Zhou and Liu [43], this model cannot produce efficiency measures directly; thus, output-oriented efficiency must be measured for each year, and the overall efficiency measure for *DMUo* must be calculated while replacing the slacks in the following equations:

$$\tau^*_{ot} = \frac{1}{1 + \frac{1}{3}\left(\frac{SDO\_NF_{ot}}{DO\_NF_{ot}} + \frac{SDO\_F_{ot}}{DO\_F_{ot}} + \frac{SUO\_CO2_{ot}}{UO\_CO2_{ot}}\right)};\ t = 2000,\ \ldots,\ 2016 \tag{4}$$

$$\tau^*_o = \frac{1}{17}\sum_{t=2000}^{2016} \tau^*_{ot} \tag{5}$$

where a country o will be globally efficient $(\tau^*_o = 1)$ if and only if $SDO\_NOF_{ot} = SDO\_F_{ot} = SUO\_CO2_{ot} = 0;\ \forall\ t = 2000, \ldots, 2016$. In other words, the country will be efficient throughout the period if it is efficient in each year. It should be noted that the evaluation of efficiency for the last year is lost because temporary interdependence is introduced into the proposed model. We chose an output-oriented measure of efficiency as we aimed to evaluate, given the set of inputs, if there were deficiencies in the desirable outputs or excesses in the undesirable output.

The production possibility set for the *DMUo* (country *o*, with *o* = 1, . . . , 24) under a CRS is defined by Equations (1)–(9).

- Equations (1)–(3) are associated with constraints on inputs:

$$GDP_{ot} = \sum_{j=1}^{24} GDP_{jt}\lambda_j^t + S\_GDP_{ot} \tag{6}$$

The *GDP* of country "*o*" must be less than or equal to the linear combination of the *GDP* of all countries in each term *t*. The difference is the slack variable of the *GDP* of country *o* in term *t* (*S_GDP*).

$$IC\_NF_{ot} = \sum_{j=1}^{24} IC\_NF_{jt}\lambda_j^t + SIC\_NF_{ot} \tag{7}$$

The non-fossil installed capacity (*IC_NF*) of country *o* must be less than or equal to the linear combination of the non-fossil installed capacity of all countries in each term *t*. The difference is the slack variable of the non-fossil installed capacity of country *o* in term *t* (*SIC_NF*).

$$IC\_F_{ot} = \sum_{j=1}^{24} IC\_F_{jt}\lambda_j^t + SIC\_F_{ot} \tag{8}$$

The fossil installed capacity (*IC_F*) of country *o* must be less than or equal to the linear combination of the fossil installed capacity of all countries in each term *t*. The difference is the slack variable of the fossil installed capacity of country *o* in term *t* (*SIC_F*).

The equation associated with the constraint on the separable desirable output is as follows:

$$DO\_NF_{ot} = \sum_{j=1}^{24} DO\_NF_{jt}\lambda_j^t - SDO\_NF_{ot}. \tag{9}$$

The electricity generation from non-fossil sources (*DO_NF*) of country *o* must be greater than or equal to the linear combination of electricity generation from the non-fossil capacity of all countries in each term *t*. The difference is the slack variable of the electricity generation from non-fossil capacity of country *o* in term *t* (*SDO_NF*).

Equations (5) and (6) capture the assumption of weak disposability between the electricity generation from fossil sources and the emission of CO_2. A variation of the non-separable desirable output is designated by $\alpha_t DO\_F_{ot}$ and is accompanied by the same proportional variation in the non-separable undesirable output designated by $\alpha_t UO\_CO2_{ot}$. Equation (5) represents the constraint on the non-separable desirable output. Equation (6) is the constraint of the non-separable undesirable output:

$$\alpha_t DO\_F_{ot} = \sum_{j=1}^{24} DO\_F_{jt}\lambda_j^t - SDO\_F_{ot} \tag{10}$$

The electricity generation from fossil sources (*DO_F*) of country *o* must be greater than or equal to the linear combination of electricity generation from the fossil capacity of all countries in each term *t*. The difference is the slack variable of the electricity generation from the fossil capacity of country *o* in term *t* (*SDO_F*).

$$\alpha_t UO\_CO2_{ot} = \sum_{j=1}^{24} UO_{CO2_{ot}}\lambda_j^t + SUO\_CO2_{ot} \tag{11}$$

The CO_2 emissions caused by the electricity generation activity (UO_CO_2) of country o must be less than or equal to the linear combination of CO_2 of all countries in each term t. The difference is the slack variable of the CO_2 of country o in term t (SUO_CO_2).

Two carry-over equations that guarantee the continuity of the link flows between the terms t and $t+1$ are as follows:

$$\sum_{j=1}^{24} IC\_NF_{jt}\lambda_j^t = \sum_{j=1}^{24} IC\_NF_{jt}\lambda_j^{t+1};\ t = 2000, \ldots, 2016 \tag{12}$$

$$\sum_{j=1}^{n} IC\_F_{jt}\lambda_j^t = \sum_{j=1}^{n} IC\_F_{jt}\lambda_j^{t+1};\ t = 2000, \ldots, 2016 \tag{13}$$

The installed capacity in non-fossil and fossil sources in each term t is determined by the respective installed capacity in term $t-1$.

The assumption of a CRS in the production possibility set is captured by the following condition:

$$\sum_{j=1}^{24} \lambda_j^t \geq 0 \tag{14}$$

Additionally, non-negativity conditions are as follows:

$$S\_GDP_t,\ SDO\_NF_t,\ SDO\_F_t,\ SIC\_NF_t,\ SIC\_F_t,\ SUO\_CO_{2t},\ \geq 0 \tag{15}$$

We test the CRS assumption using the following test introduced by Banker [44]:

$$F_j = \frac{\sum_{j=1}^{N}\left(\hat{\theta}_j^{CCR} - 1\right)^2}{\sum_{j=1}^{N}\left(\hat{\theta}_j^{BCC} - 1\right)^2} \tag{16}$$

where $\hat{\theta}^{CCR}$ is the calculated efficiency measure that assumes a CRS, as proposed by Charnes et al. [7], and $\hat{\theta}^{BCC}$ is the calculated efficiency measure that assumes a variable return to scale (VRS), as proposed by Banker et al. [45]. This calculated value is asymptotically F-distributed with (N, N) degrees of freedom. If not rejected, the CRS is accepted.

4. Results

This section is composed of two parts: in the first part, we show the descriptive statistics of the variables used for the 24 countries of the sample between 2000 and 2017; in the second part, we analyze the efficiency measure in two levels—at the aggregate level and at the country group level.

4.1. Descriptive Analysis of the Variables

Table 1 presents the mean and standard deviation of the set of data used at the country level, which was used to assess the relative efficiency of electricity generation.

Table 1. Mean and standard deviation at the country level.

Country (1)	Statistic (2)	Desirable Ouput		Undesirable Output	Input		
		Non-Fossil Gen. (3)	Fossil Gen. (4)	CO_2 (5)	GDP Per Capita (6)	Ins. Cap. Non-Fossil (7)	Ins. Cap. Fossil (8)
AR	Mean	41.00	70.00	44.23	18,412.81	11.78	20.53
	SD	3.09	16.80	9.79	2268.57	0.68	3.40
BO	Mean	2.30	3.85	3.64	5656.90	0.56	1.22
	SD	0.21	1.71	0.86	862.72	0.09	0.37
BR	Mean	400.33	62.29	40.93	14,394.79	90.36	18.26
	SD	62.27	34.45	22.37	1544.55	19.02	6.45
CH	Mean	27.04	31.03	21.45	19,981.79	6.37	9.48
	SD	3.83	8.83	6.83	3006.13	1.73	3.08
CO	Mean	43.89	13.62	9.84	11,522.65	9.78	4.63
	SD	7.07	5.65	3.53	1833.39	1.16	0.20
CR	Mean	8.62	0.42	1.50	13,297.63	1.94	0.54
	SD	1.24	0.34	0.55	1926.17	0.47	0.18
CU	Mean	0.75	15.78	10.95	10,079.38	0.45	5.25
	SD	0.17	1.74	0.90	2137.05	0.25	0.87
DR	Mean	1.71	12.01	8.83	11,363.87	0.57	2.69
	SD	0.58	2.37	1.48	2262.95	0.15	0.26
EC	Mean	10.42	7.51	5.98	9819.95	2.35	2.47
	SD	3.55	2.75	1.71	1232.25	0.85	0.69
ES	Mean	3.17	2.09	2.54	6742.26	0.75	0.74
	SD	0.64	0.34	0.50	542.44	0.15	0.17
GU	Mean	5.32	3.54	3.65	7097.37	1.36	1.51
	SD	1.66	0.62	0.50	472.13	0.61	0.28
HA	Mean	0.19	0.51	1.60	1736.84	0.06	0.21
	SD	0.07	0.27	0.26	59.55	0.00	0.04
HO	Mean	2.81	3.43	3.45	4118.70	0.75	0.94
	SD	1.00	0.90	0.56	378.25	0.35	0.23
JA	Mean	0.32	4.79	4.27	8742.39	0.09	1.03
	SD	0.15	1.41	0.99	239.61	0.04	0.17
MX	Mean	50.27	201.74	126.31	17,608.92	15.22	42.87
	SD	6.48	31.75	19.44	746.11	2.67	6.96
NI	Mean	1.32	2.07	2.55	4361.85	0.40	0.70
	SD	0.72	0.18	0.39	581.76	0.16	0.15
PN	Mean	4.46	2.69	2.95	16,470.64	1.20	0.87
	SD	1.44	0.68	0.46	4310.40	0.53	0.25
PR	Mean	54.27	0.00	1.24	9911.98	8.24	0.01
	SD	4.33	0.00	0.44	1439.28	0.64	0.01
PE	Mean	21.04	12.23	8.70	9956.29	3.67	5.05
	SD	3.61	6.89	3.92	2319.50	0.81	2.12
TT	Mean	0.01	7.56	5.83	29,570.22	0.01	1.92
	SD	0.01	1.64	0.84	4795.99	0.00	0.49
UR	Mean	8.40	1.28	2.04	16,976.87	2.01	1.02
	SD	2.71	1.12	0.91	3483.31	0.64	0.39
VE	Mean	74.21	32.30	22.05	16,547.00	14.33	11.30
	SD	9.66	6.16	4.95	2198.72	0.87	3.73
GU	Mean	0.00	0.82	1.90	6075.02	0.03	0.33
	SD	0.01	0.12	0.08	1059.76	0.01	0.04
SU	Mean	0.99	0.71	1.72	13,847.67	0.19	0.23
	SD	0.23	0.08	0.32	1846.36	0.00	0.04
TOTAL	Mean	31.79	20.51	14.1	11,845.57	7.19	5.58

Source: Own elaboration. Labels: AR: Argentina, BO: Bolivia, BR: Brazil, CH: Chile, CO: Colombia, CR: Costa Rica, CU: Cuba, DR: Dominican Rep., EC: Ecuador, ES: El Salvador, GU: Guatemala, HA: Haiti, HO: Honduras, JA: Jamaica, MX: Mexico, NI: Nicaragua, PN: Panama, PY: Paraguay, PE: Peru, TT: Trinidad and Tobago, UR: Uruguay, VE: Venezuela, GY: Guyana, SU: Suriname. Inst. Cap.: installed capacity.

- Electricity generation

In 2017, the 24 countries in the study had a total electricity generation of 1545.74 TWh, representing a growth of 63.62% compared to the year 2000, when the recorded generation was 944.73 TWh. Of the total generated by the 24 countries over the period 2000–2017, four countries contributed 74.27% (columns 3 and 4). These countries were Brazil 36.86%, Mexico 20.08%, Argentina 8.84% and Venezuela 8.49%.

During the period 2000–2017, the generation mostly originated from non-fossil sources, representing 60.78% of the total electricity generated. However, it is observed that there has been a wide variation in the share of electricity generation by types of sources. For example, in 2017, Trinidad and Tobago, Guyana and Cuba had a lower share of non-fossil sources, at 0.04%, 4.04% and 4.05%, respectively, while countries such as Paraguay, Costa Rica and Uruguay had high shares, at 100%, 99.69% and 98.42%, respectively.

- CO_2 emissions

Regarding the CO_2 emissions caused by the electricity generation sector (column 5), four countries stand out as maximum polluters: Mexico, Argentina, Brazil, Venezuela and Chile, representing 75.40% of total emissions for the analyzed period. This is due to non-fossil sources being more involved in the composition of their generation matrix, or the fact that these countries have high volumes of generated electricity.

Mexico was the country with the highest level of emissions between 2000 and 2017, with an annual average of 126.31 MTm, depending on the high level of fossil sources of the total electricity generation in the period, at 80.05%. The country with the second highest level of emissions was Argentina, with an annual average of 44.2 MTm emissions, because of the participation of fossil sources in its energy matrix, which amounted to 63.06% in the period observed. The third country with the highest level of emissions was Brazil; considering that it has been strongly oriented towards electricity generation with non-fossil sources in the period, at 86.65%, the result can be explained by its high volume of generation, annually emitting an average of 40.9 MTm. Venezuela had an annual average emission level of 22.0 MTm, which is explained by the high volume of electricity generation and by the high participation of fossil sources in the studied years, at 30.33%. Finally, Chile had an annual average of 21.45 MTm of emissions of CO_2, which could be explained by its fossil-source-dominated generation of electricity, at 53.43%.

- GDP per capita

The aggregate size of the economy of the countries analyzed, captured by the GDP, increased from $6256 billion to $9633 billion from 2000 to 2017 ($2015 PPP), indicating an aggregate growth of 53.99%.

In per capita terms, large differences can be observed between countries in the studied period. The country with the highest per capita income in 2017 was Trinidad and Tobago, with 30,347 ($2015 PPP), followed by Chile with 23,782 ($2015 PPP), while the two poorest countries were Haiti and Honduras, with per capita incomes of 1767 and 4773 ($2015 PPP), respectively.

- Installed capacity

Between 2000 and 2017, the installed capacity in the region showed an expansion of 87.89%, from 222.52 GW to 418.09 GW. In addition, the weight of the installed capacity of non-fossil sources was greater than the weight of fossil sources in the period, comprising from 59.98% to 57.34% of the total capacity in the region.

Between 2000 and 2017, Brazil was also highlighted as the country with the highest average installed capacity of non-fossil sources, at 90.36 GW, and Mexico was the country with the highest installed capacity of fossil sources, at 42.87 GW.

4.2. Electricity Generation Sector and Efficiency Measure

This subsection is composed of two parts: in the first part, we analyze the global measure of efficiency based on the spatial distribution of the measure as an aggregate; in the second part, we analyze the relative efficiency individually and expose the sources of inefficiency according to the averages of the relative slacks found by the model.

4.2.1. Aggregate Spatial Analysis of the Overall Efficiency Measure

We calculate the efficiencies with the proposed model with a CRS and with a VRS to test the assumption of a CRS following the Banker test [44]. To calculate the F value, we eliminate the measured efficiency of Guyana due to the lack of information for the first five years. Our calculated F is $1.501/7.58 = 1.981$; that is smaller than 2.014, and thus, the null hypothesis of a CRS is not rejected with a p-value of 0.05.

Figure 2 presents the spatial distribution of the overall measure of efficiency, aggregated in four ranges from the information in Table 2.

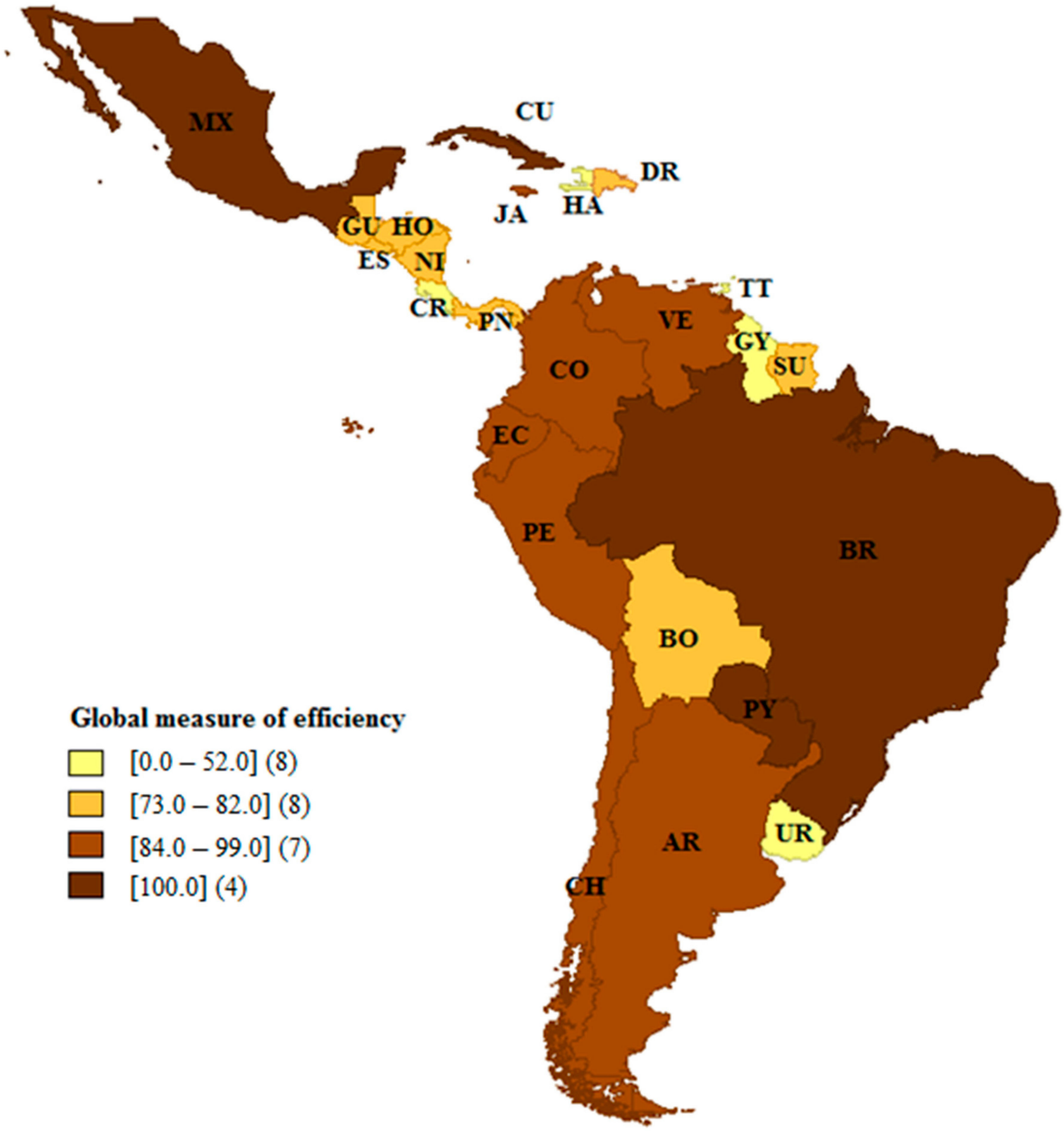


Figure 2. Global measure of efficiency of electricity generation.

Table 2. Term and global efficiency measurement.

Country	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	Global
AR	82.57	92.87	89.28	89.22	86.94	88.41	93.86	87.20	84.21	89.02	91.00	85.32	85.82	88.18	84.85	91.76	87.14	88.10
BO	72.23	75.20	84.48	72.06	75.57	76.30	78.00	82.93	81.78	84.98	84.44	85.84	85.57	88.63	83.34	89.52	73.99	80.87
BR	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
CH	88.35	97.07	97.00	95.13	97.11	98.62	99.19	95.37	95.54	98.43	91.66	96.36	85.59	87.36	96.19	92.49	82.32	93.75
CO	80.96	86.02	85.70	85.13	86.97	87.60	90.71	91.16	88.84	90.06	94.03	99.03	88.25	93.35	96.09	95.91	85.76	89.74
CR	11.03	16.72	19.35	25.09	8.55	26.95	44.67	69.01	54.52	38.03	51.40	66.42	47.83	58.37	60.37	8.36	46.70	38.44
CU	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
DR	52.14	55.06	61.06	70.57	80.78	89.76	84.41	84.16	77.76	80.68	73.01	76.56	80.83	86.63	77.78	72.44	74.69	75.20
EC	73.25	80.01	78.74	76.03	80.42	78.83	83.61	98.19	90.91	88.59	85.26	90.61	93.52	89.85	92.51	96.47	93.74	86.50
ES	66.35	69.29	71.42	73.44	72.22	76.81	84.93	91.88	79.87	79.30	75.96	74.82	75.28	74.70	77.65	77.39	75.51	76.28
GU	76.70	76.69	76.52	88.26	81.26	86.13	79.56	84.95	77.38	79.55	79.87	75.13	87.83	73.21	86.31	84.07	66.41	79.99
HA	49.96	54.90	51.31	43.44	43.94	43.90	49.87	46.78	53.38	69.43	59.01	55.05	73.85	65.90	59.47	51.53	39.60	53.61
HO	71.12	77.64	76.76	76.72	70.19	79.56	81.45	84.52	82.35	87.98	89.53	91.79	86.53	81.27	86.53	99.52	70.47	82.00
JA	69.93	59.26	52.32	59.20	70.04	99.23	97.55	95.44	94.87	95.53	96.53	94.23	92.08	90.30	90.67	91.49	87.22	84.46
MX	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
NI	64.14	70.64	79.85	70.40	70.90	76.95	63.61	65.34	75.71	76.07	76.06	76.86	95.54	68.11	71.53	74.45	74.67	73.58
PN	67.80	77.50	88.06	77.44	79.37	83.06	80.85	80.63	83.49	83.00	84.84	98.90	86.08	71.61	81.69	84.12	69.33	81.05
PY	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
PE	70.64	100.00	77.43	79.69	88.83	91.27	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	94.58
TT	45.78	59.21	54.03	36.57	55.97	99.96	99.94	88.19	95.88	81.11	27.59	39.37	25.55	24.39	26.94	26.23	22.73	53.50
UR	33.81	2.13	2.96	3.67	57.36	83.77	99.39	71.25	70.72	72.93	56.50	75.12	80.25	56.45	28.64	37.69	39.51	51.30
VE	91.57	97.67	96.33	94.93	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	98.85
GY	-	-	-	-	-	1.27	1.71	1.76	97.88	4.00	1.86	2.00	2.24	2.05	14.90	20.07	8.91	13.22
SU	65.92	68.15	67.32	62.64	62.74	64.16	72.38	70.31	72.74	78.15	100.00	78.74	89.90	100.00	100.00	100.00	77.35	78.26

Source: Own elaboration.

According to the map, it is difficult to establish a spatial pattern that contributes to the explanation of global efficiency levels for each country. However, at least three aspects can be highlighted.

On the one hand, all of the six Central American countries—Costa Rica, El Salvador, Guatemala, Honduras, Nicaragua, and Panama—belong to the two lowest global efficiency levels. On the other hand, of the five countries in the Caribbean—Cuba, Jamaica, Dominican Republic, Haiti and Trinidad and Tobago—only Cuba is in the highest global efficiency level. Finally, of the 12 South American countries, eight are in the two highest levels—Argentina, Brazil, Chile, Colombia, Ecuador, Paraguay, Peru and Venezuela—and four are in the two lowest global efficiency levels—Bolivia, Guyana, Suriname, and Uruguay.

It is worth investigating whether there is any spatial pattern in the distribution of the global efficiency measure. Moran's Index (Moran's I) is the most commonly used measure of spatial autocorrelation to describe the degree of spatial concentration or dispersion for variables included in an analysis [46]. According to Moran (1950), Moran's I is calculated as follows:

$$I = \frac{N}{S} \frac{\sum_{i=1}^{N} \sum_{j=1}^{N} w_{ij}(x_i - \overline{x})\left(x_j - \overline{x}\right)}{\sum_{i=1}(x_i - \overline{x})^2} \tag{17}$$

where N is the number of spatial units indexed by i and j; x is the variable of interest; $\overline{x}$ is the mean of x; and w_{ij} is a matrix of spatial weights such that (1) the diagonal elements w_{ii} are equal to zero and (2) the non-diagonal elements w_{ij} indicate the way that a region i is spatially connected with the region j. S is a scalar term that is equal to the sum of all w_{ij}.

When the Moran's I is positive, this implies that large values for the variable are surrounded by other large values, and when the Moran's I for a variable is negative, then the large values are surrounded by small values. Therefore, a positive spatial autocorrelation implies a spatial clustering for a variable, whereas a negative spatial autocorrelation suggests a spatial dispersion.

Figure 3 presents the Moran's I of global efficiency measures of electricity generation for 21 countries that have at least one neighbor.

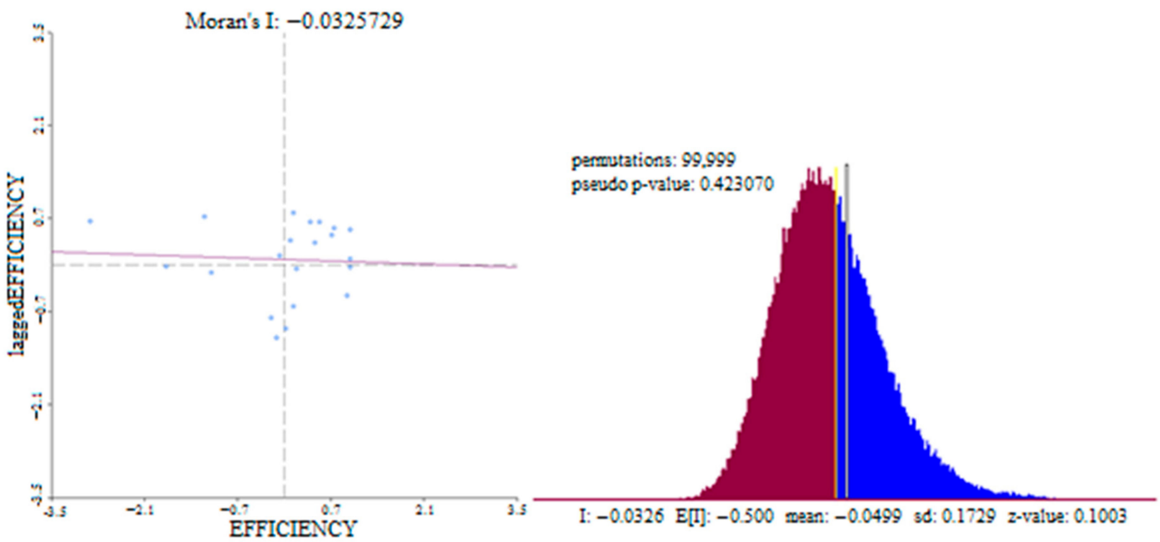


Figure 3. Moran Index of global efficiency measure of electricity generation.

According to the figure, the global efficiency measure presents a very slight negative spatial autocorrelation of −0.0326; thus, the null hypothesis of a random spatial distribution of the measure is not rejected with a p-value of 0.05.

4.2.2. Measure of Efficiency of Electricity Generation

Table 2 presents the evolution of the efficiency for each country and for each year of the period 2000–2016; in addition, it contains the global measure of efficiency for each country, which was calculated as the yearly average of efficiency.

On the left-hand side of Figure 4, we present the evolution of the efficiency of the 24 countries for the period 2000–2016, dividing them into the three groups. On the right-hand side, we show the participation of slacks for each country. Slacks can be interpreted as deficits in desirable outputs or excesses in undesirable output given the production possibilities set.

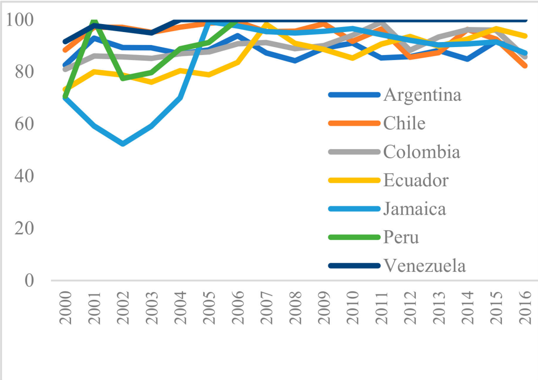
Our results confirm that, although there is currently a common agenda for Latin America to improve its energy efficiency, the incentives granted to increase efficiency have been heterogeneous throughout the countries in the region [47]. Usually, programs related to energy efficiency are led by public organizations [47], who tend to be more efficient in the development of multi-tasking than private firms [48]. Energy-efficiency entities are key to control and implement programs to support energy efficiency, but they are not enough by themselves to promote energy-efficiency improvements [47], and a complementary mechanism would be the use of incentives. There are different types of incentives that can be used to improve the energy efficiency of a country; among the most used in generation sector are mandatory performance standards and market-based and information-based incentives [49]. Mandatory codes and standards are regulatory instruments regarding energy efficiency. Market-based incentives are related to the development of auctions and tradable emission products, among others [49]. Finally, governance and support represent the final step for the implementation of energy-efficiency policies. This refers to the mechanisms used by governments in order to incentivize energy efficiency.

According to their level of efficiency, we have classified the countries into three groups: high efficiency level, medium–high efficiency level and low–medium efficiency level.

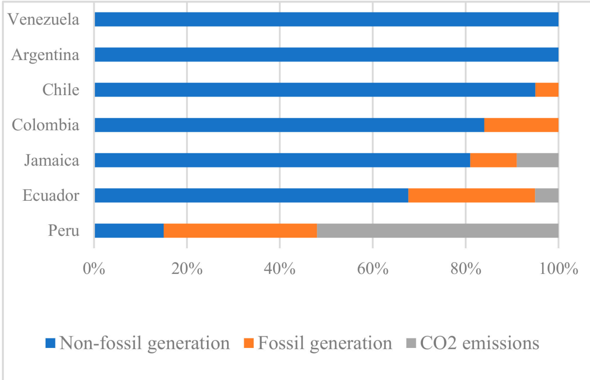
The first group is made up of 11 countries, four of which are not in the figure because they make up an efficient border and registered efficiency levels of 100 for all years; they are Brazil, Cuba, Mexico and Paraguay. These countries have an overall efficiency of 100, which is equivalent to a solution of zero slacks in each year, and implies that they have no deficiencies in desirable outputs or excesses in undesirable output given the set of inputs. In relation to Mexico and Paraguay, the results coincide with the work of Sánchez et al. [6], who found complete efficiency between 2006 and 2013 for these countries.

We highlight Mexico and Brazil because they have consolidated their institutional and regulatory frameworks to support energy efficiency activities [50], and have been recognized by IEA [51] for having a high coverage potential of regulatory instruments in terms of energy efficiency. Auctions focused on improving the efficiency of energy were conducted in the state of Roraima in Brazil [47], and also this country has implemented the Energy Efficiency Obligation Program [52]. In Paraguay, the National Committee for Energy Efficiency (CNEE) was created in 2011, which is responsible for the preparation and implementation of the National Plan for the Efficient Use of Energy [47]. Regarding Cuba, we consider that it is part of this ranking because the relationship between electricity generation, GDP and CO_2 emissions corresponds to an efficient behavior, confirming the results of Somoza et al. [53], who used a stochastic frontier as their methodology for analysis.

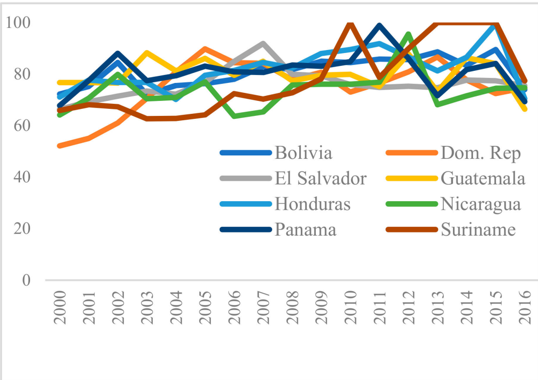
The other seven countries in the first group are Argentina, Chile, Colombia, Perú, Venezuela, Ecuador and Jamaica. In this group, a greater variability of efficiency is observed for the first years compared to the variability of the last years. For these countries, the most important source of inefficiency was non-fossil generation. In Venezuela and Argentina, their total inefficiency came from this source. Chile and Colombia presented deficiencies in the two desirable outputs, with non-fossil generation being their main source of inefficiency. Finally, Jamaica, Ecuador and Peru had deficiencies in the two desirable outputs and excesses in the undesirable output. For Jamaica and Ecuador, the main source of inefficiency was non-fossil generation followed by fossil generation, while for Peru the main source of inefficiency was CO_2 emissions followed by fossil generation.



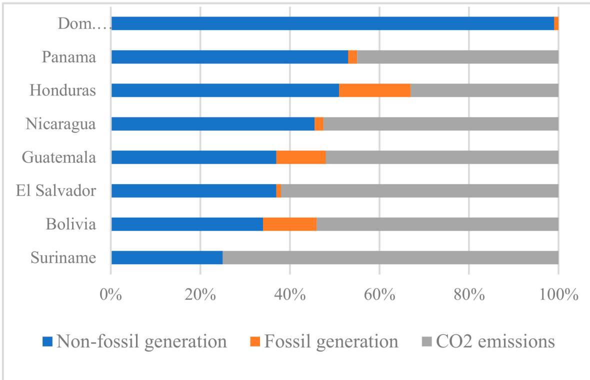
(**a**) High efficiency level Group



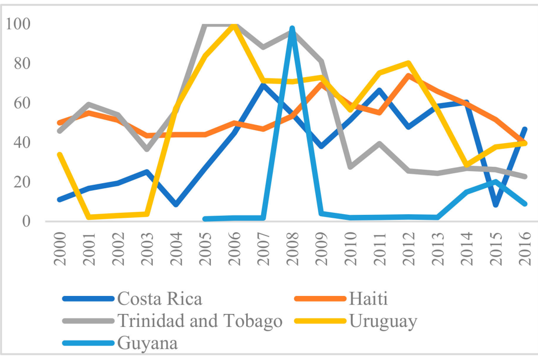
(**b**) Relative slacks of high efficiency level Group



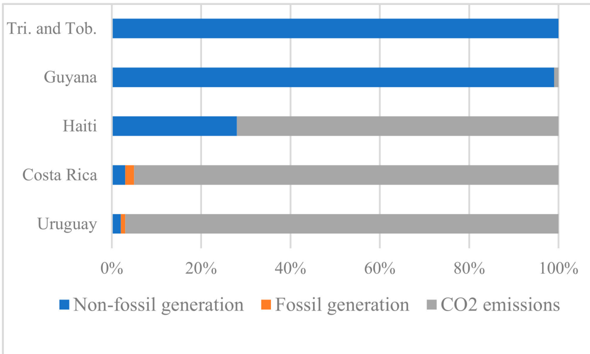
(**c**) Medium-high efficiency level Group



(**d**) Relative slacks of medium-high efficiency level Group



(**e**) Low and medium efficiency level Group



(**f**) Relative Slacks of Low and medium efficiency level Group

Figure 4. Efficiency evolution and relative slacks by groups.

We note that the level of consolidation of the institutional environment of these countries is mixed. Colombia, Perú, Venezuela and Ecuador established legal and regulatory frameworks; Colombia did this in the same year as Brazil, while Peru, Venezuela and Ecuador did this long before the other countries. Chile is currently in the process of preparing or discussing a national law, while Jamaica does not include energy efficiency in its main national laws [47]. Similar to Mexico and Brazil, Chile is recognized for having defined some regulatory instruments in terms of energy efficiency [51], and also, similar to Brazil, for having an obligation scheme [52]. Colombia is the country with the highest number of uncharged entities to regulate and monitor the energy efficiency law.

In the second group, there are eight countries with medium-high efficiency levels, ranging from 73 to 82. The countries of Bolivia, Dominican Republic, El Salvador, Guatemala, Honduras, Nicaragua, Panamá and Suriname are included in this group. This group is characterized by exhibiting an increasing trend in the evolution of efficiency and degree of convergence. However, this claim should be tested. In Suriname, Bolivia, El Salvador, Guatemala and Nicaragua, the main source of inefficiency came from CO_2 emissions followed by non-fossil generation; however, of these five, only Suriname did not present slacks in fossil generation. In Honduras and Panama, the main source of inefficiency was non-fossil generation, followed by CO_2 emissions. Finally, almost all of the inefficiency of the Dominican Republic came from non-fossil generation, and it did not present excesses in CO_2 emissions.

The legal framework in terms of energy efficiency in these countries is varied. For example, in the early 2010s, Panamá developed a national law on energy efficiency, while Nicaragua did so in the mid-decade. However, Panamá is aligned with Mexican labeling standards, while the rest of the Latin Americas countries are aligned with the programs defined in the European Union or the United States [47]. The Dominican Republic, El Salvador, Guatemala and Honduras are currently developing national laws, which are either in the process of preparation or in discussion, and we highlight the fact that the Dominican Republic and Guatemala have planned to have only one uncharged entity to regulate and monitor the national law. Finally, Bolivia is the only country that has not shown any regulatory development in this matter [47].

Finally, the last group comprises five countries with medium and low global efficiency, with scores below 54. The countries are Costa Rica, Guyana, Haiti, Trinidad and Tobago and Uruguay. Regarding Costa Rica, Uruguay and Haiti, the results coincide with those obtained by Sánchez et al. [6], who found very low efficiency levels for these countries. This group presents a very high volatility in its efficiency levels, exhibiting scores above 70 and below 25, as is the case of Uruguay, Costa Rica, Guyana and Trinidad and Tobago. In this group, the most important source of inefficiency was CO_2 emissions. Trinidad and Tobago was the only country in this group in which the inefficiency measure depended on only one component: non-fossil generation. The inefficiency of Guyana and Haiti depended on two sources—non-fossil generation and CO_2 emissions—although in Guyana, non-fossil generation was the main source of inefficiency while CO_2 emissions were predominantly responsible in Haiti. Finally, the inefficiency in Costa Rica and Uruguay was caused by deficiencies in the two desirable outputs and excesses in the undesirable output, with the latter being the main source of inefficiency. Finally, the inefficiency in Costa Rica and Uruguay was caused by deficiencies in the two desirable outputs and excesses in the undesirable output, with the latter being the main source of inefficiency. Regarding Uruguay and Costa Rica, they present an average annual efficiency of around 51 and 38, respectively, although Uruguay established both legal and regulatory frameworks in the same year as Brazil and Mexico, and Costa Rica was the first country in Latin America to define a Law of Rational Use of Energy [47]. In addition, IEA [51] did not report the coverage potential of existing mandatory codes and standards in terms of energy efficiency. Haiti and Trinidad and Tobago do not include energy efficiency in any major national laws.

5. Conclusions

In this research, we have carried out an evaluation of the evolution of the technical efficiency of electricity generation for 24 countries in Latin America and the Caribbean during the period 2010–2016. We used the DEA methodology, which allowed the evaluation of the relative efficiency of different production systems for different DMUs through a dynamic model of a CRS based on slacks and incorporated the assumption of weak disposability between electricity generation from fossil sources and CO_2 emissions. Additionally, we tested the assumption of a CRS with the test proposed by Banker (1996) and concluded that the hypothesis of a CRS was not rejected. The proposed model allowed us to establish inefficiencies in the generation methods of 20 of the 24 countries studied.

When both efficient countries and sources of inefficiency are identified, the results found in the research provide relevant information for the 20 inefficient countries, because, through learning, they can adopt best practices in the productive process of generation, with those countries that make better use of their productive capacity as reference points.

The methodology used has some advantages and disadvantages that are worth noting. The advantages mainly correspond to three aspects: (i) the method does not require an explicit mathematical specification for the production or cost function, (ii) it can handle multiple inputs and outputs simultaneously and (iii) the source of the inefficiency can be identified, quantified and analyzed for each DMU.

Regarding the disadvantages, five aspects are particularly important: (i) the results are sensitive to the selection of inputs and outputs, (ii) as a non-parametric technique, the best specification cannot be corroborated, (iii) the number of efficient DMUs increases with the number of inputs and outputs, (iv) the measurement of efficiency is sensitive to outliers, and (v) the dynamic DEA assumes implicitly that there is no technological change over time. Regarding the first disadvantage, in this research, we did not have access to information associated with the labor used in the generation of electricity in each country, which, without a doubt, is an important productive factor of the activity. Therefore, for future studies, it would be interesting to introduce this variable, as previously incorporated in the study of Bi et al. [22].

Another important point is that this study focuses solely on the measurement of the technical efficiency of electricity generation, leaving aside the evaluation of the efficiency of allocation. Because of this, we did not consider the electricity rates in each country. The countries found in this study to be the most efficient do not have lower rates per unit of electricity than those that are less efficient (in terms of technical efficiency). Besides, the total losses of electricity in the transmission and distribution systems are not considered; therefore, the study does not include an evaluation of the efficiency of the electricity systems.

Finally, the results suggest that the most efficient countries have developed an institutional and legal context for energy efficiency, accompanied by other market incentives, as well as information mechanisms to improve energy efficiency. While less-efficient countries have developed the legal context recently or do not plan to do so yet, these types of countries should implement the strategies of Brazil or Mexico, which border these countries.

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Nomenclature

DEA	Data envelopment analysis
DMU	Decision-making units
GHG	Greenhouse gases
GW	Gigawatt
TWh	Terawatt-hours
MTm	Million metric tons
DO_NF	Desirable output: non-fossil generation
DO_F	Desirable output: fossil generation
GDP	Gross Domestic Product
IC_NF	Installed capacity: non-fossil sources
IC_F	Installed capacity: fossil sources
SDO_NF	Slack associated with desirable output: non-fossil generation
SDO_F	Slack associated with desirable output: fossil generation
SUO_CO_2	Slack associated with undesirable output: CO_2 emissions
S_GDP	Slack associated with GDP per capita
SIC_NF	Slack associated with installed capacity: non-fossil sources
SIC_F	Slack associated with installed capacity: fossil sources

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