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Port Efficiency Incorporating Service Measurement Variables by the BiO-MCDEA: Brazilian Case

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Abstract: Data envelopment analysis (DEA) has many advantages for analyzing the efficiency of decision-making units, as well as drawbacks, such as a lack of discrimination power. This study applied bi-objective multiple-criteria data envelopment analysis (BiO-MCDEA), a programming approach used to overcome the limitations of traditional DEA models, to analyze the efficiency of 20 Brazilian ports with a consideration of six input and one output variables from 2010 to 2016. Two time-related variables were included to reflect current problems faced by Brazilian ports experiencing long wait times. The results reveal a significant disparity in port efficiency among Brazilian ports. The top five most efficient ports are those with the highest cargo throughput. A clustering analysis also confirmed a strong correlation between cargo throughput and port efficiency scores. Total time of stay, pier length, and courtyard also had strong correlations with the efficiency scores. The clustering method divided Brazilian ports into three groups: efficient ports, medium efficient ports, and inefficient ports.

Keywords: data envelopment analysis (DEA), bi-objective multiple-criteria data envelopment analysis (BiO-MCDEA), cluster analysis; Brazil; port efficiency

1. Introduction

Ports play an essential role in the economic development of countries with access to sea or waterways by connecting them to international markets. Brazil's ports are no exception: 95% of the flow of Brazilian imports and exports occur through ports, demonstrating the importance of the port sector to the national economy [1]. Increasing port efficiency is crucial for lowering logistics costs for Brazilian companies, which account for 11.73% of total revenue, higher than in the United States and China [2]. Brazil ranked 162 among 264 countries for port infrastructure quality [3]. In 2012, the waiting time for container vessel berthing in Santos port was 16 h on average, and was increasing [4]. Such delays increase logistics costs in the overall supply chain and service unreliability [5]. According to the United Nations Conference on Trade and Development (UNCTAD) [6], the biggest concern for most shippers was on-time delivery. Thus, service time and services costs are important factors for shippers and logistics providers.

Bureaucracy along with underdeveloped infrastructure is a main cause of the inefficiency of Brazilian ports. The Brazilian government has attempted to eliminate these problems through private investments [7]. In 1993, Brazil established law 8630/93, the so-called "Port Modernization Law," enabling port investment by private companies through a lease contract, which resulted in significant improvements in the Brazilian port sector [8]. Consequently, Brazilian ports reduced handling costs of containers by 53% from 1997 to 2003 [1].

Brazil has 34 public ports and more than 140 private port terminals, including maritime and river ports. The public ports are administrated by the Secretary of Ports (SEP) of the Ministry of Transport. The SEP is responsible for all policies, programs, and projects to support the development of the Brazilian port system. Of the 34 public ports, 16 are administered by state or municipal governments, and the other 28 are managed by terminal companies—joint venture companies, of which the main shareholder is the federal government [9]. Because of the data limitation, port ownership was not considered in this research. Therefore, the scope of the research only covers the public domain. Estimating performance of the private port and comparing with public sector will be the next topic of our forthcoming project. Although private-sector port investment is increasing, public ports are still playing gateway roles for international maritime trade in Brazil. Given the importance of public ports and the limited data available from private terminals, this study analyzes the efficiency of selected public ports only.

The two research questions of our interest are to improve the discrimination power of the previous MCDEA results of Brazilian ports by applying BiO-MCDEA model and develop the service measurement by incorporating time variables of port operation to reflect the case of Brazilian ports. Having established the status quo of Brazilian ports as a whole, this study analyzes the efficiency of 20 Brazilian public ports from 2010 to 2016. BiO-MCDEA is used to discriminate among the ports' efficiency performance levels. The study carefully selects their input and output variables to reflect port infrastructure and operations, taking into account time-related variables as service-measuring instruments.

In addition, cluster analysis is used to classify Brazilian ports into three groups based on efficiency and several explanatory variables: efficient ports, medium efficient ports, and inefficient ports. Based on the cluster analysis, the relationships between efficiency and important input variables are examined and discussed. Hierarchical clustering is used as the cluster analysis method.

2. Literature Review

2.1. DEA Application on Port Study

Data envelopment analysis, developed by Charnes et al. [10], uses a linear programming approach to measure the efficiency of decision-making units (DMUs) based on input and output variables. There are numerous studies on port performance measurement, most of which have used the typical DEA or stochastic frontier analysis (SFA). Roll and Hayuth [11] are considered to be the first to apply DEA to port research. However, no empirical data were collected and analyzed in that study. Later, Tongzon [12] pointed out that previous econometric measures of port efficiency could estimate only one output variable. Therefore, he suggested an overall measure for efficiency comparisons across ports by using the DEA method on a sample of Australian and other international ports and demonstrated the suitability of the DEA method for port efficiency estimation. Martinez-Budria et al. [13] applied a DEA-BCC (Banker, Charnes, and Cooper) model to estimate the efficiency of 26 Spanish ports using empirical panel data from 1993 to 1997. The result indicated that ports' performance levels could be differentiated according to their level of "complexity," defined as high, medium, or low. They showed that while the efficiency of high-complexity ports increased over time, that of medium- and low-level ports did not. Cullinane et al. [14] applied DEA-BCC and DEA-CCR (Charnes, Cooper, and Rhodes) models to panel data to explain how port performance evolved.

Recently, regression techniques have been applied to observe how certain factors affect port efficiency. Yuen et al. [15] applied DEA-BCC and DEA-CCR models to estimate efficiency scores for Chinese ports and used Tobit regression to investigate the impact of ownership structure and port competition on port performance. They found that intra- and inter-port competition, and government ownership, enhanced the efficiency of Chinese ports. Wan et al. [16] also applied a two-stage DEA and Tobit regression method to analyze the impact of hinterland accessibility, represented by rail facility and road congestion, on US container port productivity. Chang et al. [17] analyzed whether the Emission Control Area (ECA) regulation reduced the productivity of 58 European container ports. They used a slack-based measure (SBM) DEA model and applied a bootstrapped truncated regression, rather than a Tobit model, to correct the bias arising from the data-generating process.

2.2. Discrimination Power Issues in DEA

Although the DEA method has been a popular way to evaluate port performance, its lack of discrimination power among efficient DMUs is considered a drawback [18]. Therefore, Barros [19] applied cross-efficiency and super-efficiency methods in his port study to address the lack of discrimination power of DEA-CCR and DEA-BCC models. Barros [19] evaluated the efficiency of 24 Italian ports via his DEA-BCC model and found 17 efficient DMUs (i.e., with a score of 1). This result was considered to have less discrimination power. Thus, applying a cross-efficiency and super-efficiency approach modified the scores, which had different values beyond the boundaries of the basic DEA model (i.e., 0 to 1). Oliveira and Cariou [20] also applied a super-efficiency DEA model to evaluate the performance of 122 iron ore and coal ports. They compared results between a basic DEA and super-efficiency model and presented the discrimination power differences between them. The results showed that efficient DMUs (which scored 1 in the CCR model) differed from the super-efficiency model by 50.8%.

Despite many research attempts, the supper efficiency and cross-efficiency models were both found to be insufficient for improving the discrimination power of the DEA [21–25]. The super-efficiency DEA model fails when some of the input variables are zero [26]. The cross-efficiency model is computationally expensive because it can provide many optimal solutions due to the DEA weight non-uniqueness [27]. Therefore, the multiple-criteria DEA (MCDEA) using a "non-dominated" solution approach was suggested by Li and Reeves [28]. They proposed MCDEA model with three objectives, i.e., minimizing the inefficiency, the maximum deviation, and the sum of deviation, to overcome weight dispersion and discrimination power problems. Bal et al. [29] proposed goal programming and DEA (GPDEA) to solve the three objectives of the MCDEA simultaneously. This GPDEA model improved discrimination power and the dispersion of weights in an MCDEA framework. However, Ghasemi et al. [30] found that GPDEA models were invalid, claiming that the original formulation and the results in Bal et al. [29] had glitches. Ghasemi et al. [30] corrected the results of Bal et al. [29] and proposed a bi-objective multiple-criteria DEA (BiO-MCDEA) model.

Few studies have focused on measuring Brazilian ports' efficiency while addressing the discrimination power of the DEA approach [31,32]. To fill this research gap, this study applies the BiO-MCDEA to Brazilian ports to improve the discrimination power of the MCDEA and to outperform the GPDEA model in terms of weight dispersion and discrimination power. In addition, the BiO-MCDEA is preferable to the GPDEA model because it requires fewer computational codes.

2.3. Brazilian Port Performance

In 2006, Rios and Maçada [33] pointed out that no studies had examined Brazilian ports' performance. Wanke et al. [34] conducted what was probably a pioneering study of Brazilian seaport performance by applying DEA and SFA models. They found that most of the Brazilian ports showed increasing returns to scale and that the type of cargo handled played an important role in determining port performance. Barros et al. [35] analyzed the productivity of Brazilian ports using a Malmquist index with technological bias from 2004 to 2010. They indicated that the traditional development accounting method was not suitable for estimating productivity changes in Brazilian ports. Wanke [36] used a two-stage network-DEA model to investigate the physical infrastructure and shipment consolidation performance of Brazilian ports. He found that private administration had positive impacts on physical infrastructure performance and that cargo diversity and hinterland size also had positive impacts on consolidation efficiency. Wanke and Barros [37] applied a bootstrapping technique to the DEA and analyzed 27 major Brazilian ports with data covering 2007 to 2011. They asserted that Brazilian ports suffered from capacity shortfalls and that connectivity infrastructure had a positive impact on scale efficiency.

Rubem et al. [38] applied the GPDEA in a port study to analyzeBrazilian container ports in 2013 and showed that their performance levels were homogeneous. However, this result was based on an insufficient number of DMUs, and Ghasemi et al. [30] pointed out that the GPDEA lacked discrimination power. Table 1 shows a summary of applications of DEA to port studies.

Table 1. Applications of DEA to Ports.

Author(s) (year)	Data	Input Variables	Output Variables	Model
Roll and Hayuth (1993) [11]	Hypothetical example of 20 ports	Manpower, Cargo uniformity, Capital	Service level, Cargo throughput, Ship calls, Consumer satisfaction	DEA-CCR model
Martinez-Budria et al. (1999) [13]	26 Spanish ports, 1993–1997	Labor expenditure, Other expenditure, Depreciation charges	Port facility rent revenue, Total cargo moved through docks	DEA-BCC model
Tongzon J. (2001) [12]	4 Australian ports and 12 international ports, 1996	Number of container berths, Number of cranes, Number of tugs, Labor, Terminal area, Delay time	Ship working rate, Cargo throughput	DEA-CCR additive model
Cullinane et al. (2006) [14]	27 ports in the world in 2001	Terminal length, Terminal area, Quayside gantry, Yard gantry, Straddle carrier	Container throughput	DEA-CCR, BCC model, and SFA
Yuen, Zhang, and Cheung (2013) [15]	21 ports in China and its neighboring countries 2003 and 2007	Berth, Total length, Port land area, Quay crane, Yard gantries	Throughput	DEA-CCR and tobit regression
Wan, Yuen, and Zhang (2014) [15]	13 US container ports from 2000 to 2009	Container terminal size, Total length of berths, Total number of cranes and gantries	Throughput	DEA-CCR, BCC model, and tobit regression
Chang et al. (2018) [17]	58 European container ports	Berth length, Total number of container crane, Total area	Throughput	SBM DEA model and bootstrapped truncated regression model
Wanke (2013) [36]	27 major Brazilian ports in 2011	Number of berths, Warehousing area, Yard area	Solid bulk throughput, Container throughput	Network-DEA model
Wanke and Barros (2016) [37]	27 major Brazilian ports from 2007 to 2011	Quay length, Maximal quay depth, Number of berths, Warehousing area, Yard area, Channel depth	Dry bulk loading hours, Container loading hours, Dry bulk throughput, Container throughput, Container frequency	CRS and VRS model with bootstrapping technique
Rubem et al. (2015) [38]	4 Brazilian ports in 2013	Berth length, Maximum draft, Storage area	Container cargo handled	GPDEA

This study expands the literature in two ways. First, it applies a robust bi-objective MCDEA, which improves the discrimination power of the DEA model, to a port study. Second, by using this method to analyze 20 Brazilian public ports, this study provides a more accurate estimation of efficiency across Brazilian ports than previous studies have offered.

Cluster analysis is widely used in data science to create meaningful groups based on similarity from a multivariate dataset. It is the process of grouping a set of objects in such a way that objects in the same group (called a "cluster") are more similar to each other than they are to those in the other groups [39].

Cluster analysis was recently applied to evaluate the competitiveness of Brazilian ports. Maria Rios and de Sousa [40] used cluster analysis to classify 17 Brazilian container terminals into three distinct groups based on competitiveness criteria using a hierarchical cluster analysis. Tovar and Rodríguez-Déniz [41] reviewed the literature on classification methods for port efficiency and applied a frontier-based clustering approach to classify Brazilian ports for efficiency benchmarking.

3. Methodology: BiO-MCDEA

Data envelopment analysis has two drawbacks, weak discriminating power and an unrealistic weight distribution, which are interrelated and sometimes occur together [28]. Banker et al. [42] suggested that avoiding the weak discriminating power requires following the "golden rule" to determine the number of DMUs according to the number of input and output variables selected for the model. However, the golden rule cannot be followed for models in which the number of DMUs is not greater than three times the product of the number of input and output variables. Consequently, the model has weak discrimination power, leading it to identify an excessive number of DMUs as efficient. The other problem is the unrealistic weight distribution. Some DMUs are classified as efficient in the classical DEA model because they have excessively large weights in a single output and/or excessively small weights in a single input while not being unrealistic [28].

Many researchers have connected the DEA to the MCDEA model to improve the discriminating power of the classical DEA. Li and Reeves [28] suggested an interaction approach for solving the three objectives analyzed separately, one at a time, with no preference order set for the objectives listed by Ghasemi et al. [30]. The aim of their proposed MCDEA model solution process is not to extract an optimal solution but instead to find a series of non-dominated solutions, from which the analyst may select the preferred solution [30]. Ghasemi et al. [30] developed the BiO-MCDEA to introduce a weighted model to improve the discrimination power and weight dispersion of the MCDEA. Ghasemi et al. [30] used the BiO-MCDEA to find not only the optimal solution for each objective function but also the optimal solution that optimized all the objectives at the same time. For this purpose, the author used goal programming to solve the new DEA model. The BiO-MCDEA CCR oriented to input is expressed as follows:

$$\text{Minimize } h = \left(w_2 M + w_3 \sum\nolimits_{j=1}^{n} d_j\right) \tag{1}$$

$$\text{Subject to}: \sum\nolimits_{i=1}^{m} v_i x_{io} = 1 \tag{2}$$

$$\sum\nolimits_{r=1}^{s} u_r y_{rj} - \sum\nolimits_{i=1}^{m} v_i x_{ij} + d_j = 0 \tag{3}$$

$$M - d_j \geq 0 \tag{4}$$

$$u_r \geq \varepsilon \tag{5}$$

$$v_i \geq \varepsilon \tag{6}$$

$$d_j \geq 0 \tag{7}$$

Let input matrix X = [x_{ij}, $i = 1, 2, \ldots, m$, $j = 1, 2, \ldots, n$] and output matrix Y = [y_{rj}, $r = 1, 2, \ldots, s$, $j = 1, 2, \ldots, n$]. j is the number of DMUs being compared in the DEA analysis. i is the number of inputs used by the DMUs. r is the number of outputs. u_r is a coefficient or weight assigned by the DEA to output r. v_i is a coefficient or weight assigned by the DEA to input i. Then, x_{ij} is an input variable, y_{rj} is an output variable, d_j is a deviation variable, and M is the maximum quantity of all deviation variables. We set w_2 and w_3 as equal to 1 and set ε as 0.

This study uses BiO-MCDEA oriented to input, which reduces the input and retains the same output value. Since the two input variables are related to time, a decrease in total time is expected. Time values are even more significant for Brazil, where long queues are common. Using an input-oriented model makes it possible to determine the variables that are most important for the efficiency score, which is the objective of this study. As mentioned in the introduction, Brazilian ports need to improve their efficiency of operation and infrastructure before seeking to increase their total cargo. Such improvement will ultimately increase cargo throughput. Thus, an input-oriented approach was selected.

4. Data and Variable Selection

4.1. Database

The dataset contains 20 public ports: Santos, Itaguaí, Paranaguá, Rio Grande, Suape, São Franc. Sul, Vitória, Aratu, Fortaleza, Salvador, Belém, Imbituba, Santarém, Maceió, Cabedelo, Recife, Antonina, São Sebastião, Ilhéus, and Natal. Only public ports are considered in this analysis, and all 20 of the selected ports are classified as seaports by The National Agency for Water Transportation (ANTAQ). Two of the ports in northern Brazil are located along the Amazon River but are nevertheless classified as seaports by ANTAQ due to the high depth of the river, which allows oceanic vessels to navigate through its channel.

The data on the time components and total cargo are collected from ANTAQ's website (web.antaq.gov.br). ANTAQ has developed the Port Performance System to collect data on port operations and their respective pricing. Cargo data are collected from the Yearbook of the National Confederation of Transport. Data on port infrastructure are collected from the ports' official websites. Data on port infrastructure are collected from WebPortos (webportos.labtrans.ufsc). For a better understanding of the data, the table with input and output data for all of 20 analyzed ports are attached to Tables A1–A3.

4.2. Variable Selection

The variables are selected based on prior research on Brazilian ports' efficiency using DEA. Variables for berth length of all the terminals in the port and depth(draft) of the whole port are selected to reflect the handling capacity of the ports, considering the current trend of increasing average vessel sizes. Previous literature of Tongzon J. (2001) and Chang et al. (2018) used the number of cranes to analyze the container terminal efficiency and this approach is common in port performance research because it can be the proxy of the labor input. In this research, DMU is determined by port level, which consider not only container terminal but other various cargo terminals. Therefore, the number of container cranes were not taken as input variable [12,17]. Variables for total space of the warehouse area and yard area are selected to consider the cargo handling capacity of the port terminals, which is directly related to how much cargo the ports can handle.

Time-related variables are considered to reflect Brazilian ports' unique long waiting queues. Tongzon and Oum [43] emphasized that port efficiency is often reflected in the speed and reliability of port services such as on-time berthing, guaranteed vessel turnaround times, and guaranteed container connection. However, only a few studies have considered time-related variables in analyses of port efficiency [12,44].

Ship turnaround time is an important criterion for evaluating the efficiency of port operations and service quality. This comprises the time elapsed between a ship's entry into port and its departure, including unloading and loading time. Ship turnaround time thus reflects port performance in aggregate [5]. It consists of the wait time for berthing, the wait time before operations begin, the operation time, and the wait time for undocking [45]. This study incorporates two time variables: waiting time before berthing(T1) and total time at berth(T5) as service-measuring variables (see Figure 1).

The ANTAQ database collects and maintains the data on the turnaround time components for two cargo types, which are specified by container cargo and commodity cargo. The database explains that the commodity cargo is composed of loose bulk, liquid bulk, and loose cargo. Although the word commodity cargo is not an official term, we decided to follow the term of the original data source because of the structure of the collected data, which cannot be subdivided. Since this study considers all types of cargo to measure the ports' total efficiency, it considers the average of the time values for the two cargo types. For ports that do not operate container ships, only the data related to the handling of commodity cargo are considered.

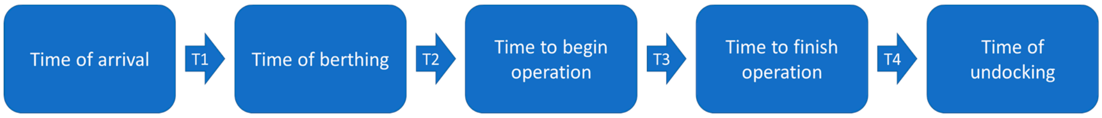

Figure 1. Components of total turnaround time.

- Wait time for berthing (T1)
- Wait time before operations begin (T2)
- Operation time (T3)
- Wait time for undocking (T4)
- Total time at berth (T5) = T2 + T3 + T4
- Total turnaround time = T1 + T2 + T3 + T4

4.3. Pearson Correlation

Charnes et al. [46] claimed that the input and output data in the DEA are meaningful only when they satisfy isotonicity. In other words, the output should increase when the input increases. Correlation analysis is used to analyze the correlation between the input and output variables. The result is presented in Table 2.

Table 2. Pearson correlation results.

	Berth Length (m)	**Draft (m)**	**Warehouse (m^2)**	**Yard (m^2)**	**Total Time at Berth**	**Waiting Time**	**Total Cargo (ton)**
Berth length	1.00	0.00	0.72	0.47	−0.37	0.12	0.84
Draft	0.00	1.00	0.06	0.56	−0.15	0.11	0.33
Warehouse	0.72	0.06	1.00	0.38	−0.28	0.13	0.61
Courtyard	0.47	0.56	0.38	1.00	−0.41	0.15	0.82
Total time at berth	−0.37	−0.15	−0.28	−0.41	1.00	0.05	-
Wait time	0.12	0.11	0.13	0.15	0.05	1.00	0.22
Total cargo	0.84	0.33	0.61	0.82	−0.43	0.22	1.00

The Pearson correlation shows two input variables (port draft and wait time) with low correlations. However, they are not excluded because the literature review suggests the following. First, the draft of Brazilian ports is not as deep as that of Asian and European ports. This prevents large vessels from docking in them. Increasing drafts is one of the major works Brazilian ports are currently pursuing. Second, wait time is not excluded because UNCTAD and other important researchers have argued the importance of including time variables. There is one negative correlation between dwell time and total cargo handled at the port. According to Wang et al. [47], "a Pearson correlation are used to make sure the relationship between input and output factors is isotonicity, which means that if the input quantity increases the output quantity could not decrease under the same condition." This study considers dwell time as an input and total cargo as an output. If the dwell time increases, cargo quantity will decrease. As this scenario is inconsistent with the Pearson correlation, the correlation between these two variables showed negative results, despite the positive correlation. Table 3 lists the selected input and output variables.

Table 3. Compilation of input and output variables.

Input	Output
Berth length (m)	Total cargo throughput (tons)
Draft (m)	
Warehouse (m^2)	
Yard (m^2)	
Total time at berth (h)	
Waiting time (h)	

5. Results and Discussion

5.1. Results of DEA Analysis

The BiO-MCDEA CCR shows a significant disparity among the Brazilian ports. Only the Santos port is efficient in 2016, and four other ports—Itaguaí, Paranaguá, Suape, and Rio Grande—had efficiency scores that can be considered intermediate. The difference between these ports and the remaining ports can be considered significant, as is evident in Table 4: 75% of the ports have very low efficiency scores, ranging from 0 to 0.33.

The BiO-MCDEA's discrimination power makes it more difficult for a DMU to be considered efficient than in the classical DEA. Consequently, the efficiency scores of all DMUs except for Santos are all lower than in the results of classical DEA models, as shown in Table 4. The classical DEA model considered eight ports efficient, accounting for 40% of the ports. When 40% of the DMUs have a 100% score, it is more difficult to perform an in-depth analysis of port efficiency. The four least-efficient ports (i.e., Ilhéus, Maceió, Recife, and Antonina) and the five most efficient ports are the same for the BiO-MCDEA CCR and classical DEA-CCR. The difference lies in the ports' scores. With the BiO-MCDEA, it is possible to distinguish between them due to the greater differentiation among the efficiency scores. This enables a more precise ranking, especially for the eight ports with the same efficient scores in the classical DEA model.

Table 4. Comparison of efficiency scores between BiO-MCDEA CCR and DEA (2016).

Port	Efficiency Score	
	DEA-CCR (2016)	BiO-MCDEA CCR (2016)
Santos	1	1
Itaguaí	1	0.46
Paranaguá	1	0.92
Rio Grande	1	0.56
Suape	1	0.76
São Franc. do Sul	1	0.27
Vitória	0.38	0.21
Aratu	0.68	0.09
Fortaleza	0.37	0.33
Salvador	0.72	0.22
Belém	1	0.21
Imbituba	0.27	0.06
Santarém	1	0.02
Maceió	0.16	0.01
Cabedelo	0.31	0.03
Recife	0.2	0
Antonina	0.21	0.01
São Sebastião	1	0.02
Ilhéus	0.05	0
Natal	0.23	0.02

Table 5 shows the efficiency scores for 20 ports in 2016 using the BiO-MCDEA CCR and the BiO-MCDEA BBC. Santos and Belém were considered efficient by the BiO-MCDEA BCC. Belém is considered "inefficient" by the BiO-MCDEA CCR model, with an efficiency score of 0.21, while the BiO-MCDEA BCC model considers it "efficient," with a score of 1.

The CCR model assumes constant returns to scale (CRS), while the BCC model assumes variable returns to scale (VRS). The two concepts are distinguished based on the relationship between the size of the investment and the return. The perspective of the CCR assumption is that the return increases at the same rate at which the investment grows, while the perspective of the BCC assumption is that the return will continue to change at a rate different from the rate at which the investment grows. Thus, the shape of the frontier, which determines the efficiency scores of the DMUs in the DEA model, could change, and the efficiency score could also change. Therefore, under the CRS assumption, Belém is inefficient; under the VRS assumption, however, Belém is deemed an efficient DMU. According to the input variables, Belém has one of the shortest total berth times and a wait time of zero hours.

Table 5. Port efficiency scores in BiO-MCDEA CCR and BiO-MCDEA BCC in 2016.

Port	BiO-MCDEA CCR		BiO-MCDEA BCC	
	Efficiency Score	**Condition**	**Efficiency Score**	**Condition**
Santos	1	Efficient	1	Efficient
Itaguaí	0.46	Intermediate	0.53	Intermediate
Paranaguá	0.92	Intermediate	0.81	Intermediate
Rio Grande	0.56	Intermediate	0.62	Intermediate
Suape	0.76	Intermediate	0.75	Intermediate
São Franc. do Sul	0.27	Inefficient	0.69	Intermediate
Vitória	0.21	Inefficient	0.37	Inefficient
Aratu	0.09	Inefficient	0.56	Intermediate
Fortaleza	0.33	Inefficient	0.61	Intermediate
Salvador	0.22	Inefficient	0.58	Intermediate
Belém	0.21	Inefficient	1	Efficient
Imbituba	0.06	Inefficient	0.25	Inefficient
Santarém	0.02	Inefficient	0.59	Intermediate
Maceió	0.01	Inefficient	0.07	Inefficient
Cabedelo	0.03	Inefficient	0.64	Intermediate
Recife	0	Inefficient	0.12	Inefficient
Antonina	0.01	Inefficient	0.32	Inefficient
São Sebastião	0.02	Inefficient	0.38	Inefficient
Ilhéus	0	Inefficient	0.12	Inefficient
Natal	0.02	Inefficient	0.66	Intermediate

The efficiency scores for all ports from 2010 to 2016 in the BiO-MCDEA CCR and BiO-MCDEA BCC models are shown in Tables 6 and 7, respectively.

Table 6. Port efficiency scores in BiO-MCDEA CCR for 2010–2016.

DMU (%)/year	2010	2011	2012	2013	2014	2015	2016
Santos	1	1	1	1	1	1	1
Itaguaí	0.46	0.45	0.5	0.39	0.5	0.39	0.46
Paranaguá	0.91	0.89	0.92	0.69	0.9	0.81	0.92
Rio Grande	0.55	0.51	0.47	0.4	0.6	0.52	0.56
Suape	0.31	0.38	0.39	0.39	0.52	0.64	0.76
São Franc. do Sul	0.05	0.26	0.31	0.37	0.3	0.17	0.27
Vitória	0.25	0.29	0.24	0.16	0.24	0.21	0.21
Aratu	0.18	0.09	0.13	0.08	0.05	0.08	0.09
Fortaleza	0.31	0.32	0.33	0.3	0.33	0.27	0.33

Table 6. *Cont.*

DMU (%)/year	2010	2011	2012	2013	2014	2015	2016
Salvador	0.14	0.06	0.13	0.16	0.21	0.19	0.22
Belém	0.3	0.31	0.29	0.25	0.25	0.22	0.21
Imbituba	0.02	0.04	0.02	0.02	0.05	0.05	0.06
Santarém	0.03	0.06	0.08	0.11	0.06	0.04	0.02
Maceió	0.28	0.28	0.25	0.17	0.2	0.16	0.01
Cabedelo	0.01	0.04	0.06	0.02	0.03	0.02	0.03
Recife	0.01	0.01	0.01	0.01	0.01	0.01	0
Antonina	0	0.01	0.01	0.01	0.02	0	0.01
São Sebastião	0	0.02	0	0.02	0.03	0.03	0.02
Ilhéus	0	0	0	0	0	0.01	0
Natal	0	0.01	0	0	0	0	0.02

Table 7. Port efficiency scores in BiO-MCDEA BCC for 2010–2016.

DMU (%)/year	2010	2011	2012	2013	2014	2015	2016
Santos	1	1	1	1	1	1	1
Itaguaí	0.58	0.49	0.47	0.45	0.54	0.44	0.53
Paranaguá	0.82	0.77	0.86	0.64	0.79	0.82	0.81
Rio Grande	0.63	0.5	0.39	0.53	0.62	0.53	0.62
Suape	0.52	0.46	0.55	0.59	0.56	0.64	0.75
São Franc. do Sul	0.21	0.69	0.69	0.71	0.71	0.72	0.69
Vitória	0.26	0.4	0.36	0.36	0.43	0.39	0.37
Aratu	0.57	0.54	0.54	0.4	0.11	0.55	0.56
Fortaleza	0.62	0.6	0.6	0.61	0.61	0.61	0.61
Salvador	0.58	0.56	0.56	0.57	0.57	0.58	0.58
Belém	1	1	1	1	1	1	1
Imbituba	0.17	0.18	0.17	0.22	0.19	0.22	0.25
Santarém	0.52	0.56	0.56	0.58	0.56	0.54	0.59
Maceió	0.73	0.72	0.71	0.71	0.71	0.72	0.07
Cabedelo	0.65	0.63	0.63	0.5	0.63	0.64	0.64
Recife	0.13	0.23	0.27	0.26	0.32	0.17	0.12
Antonina	0.14	0.05	0.05	0.08	0.34	0.23	0.32
São Sebastião	0.63	0.36	0.15	0.38	0.38	0.4	0.38
Ilhéus	0	0.26	0.22	0.31	0.21	0.3	0.12
Natal	0	0.65	0.65	0.25	0.44	0.61	0.66

Santos port, the highest-ranked in terms of cargo throughput, handled 33% of all cargo that passed through Brazilian public ports in 2016, followed by Itaguaí (20%), Paranaguá (14%), and Rio Grande and Suape (8%). These five ports together moved 83% of the cargo that passed through public ports in 2016. It can be seen that there is no balanced distribution between Brazilian ports.

The five most efficient ports in the BIO-MCDEA CCR model are also the ports with the highest cargo throughput, as shown in Figures 2 and 3. As ports with larger physical infrastructure can handle more cargo than small ports, production capacity and output value are correlated.

5.2. Cluster Analysis of Ports

When a pattern is identified, as in the case between efficiency and total cargo throughput, a more in-depth analysis using other methodologies can complement or affirm the result of the initial analysis. In this case, a clustering method is used since it makes it possible to visualize how ports can be grouped according to similar characteristics, and how far clusters are located from each other. It is also possible to analyze what makes these clusters different from each other. Hierarchy clustering is carried out using Python. Efficiency scores and total cargo throughput are used for the clustering.

A dendrogram is generated to determine the optimal number of clusters. It shows the distance between the port in the graph and how these ports are connected to form the cluster according to proximity. For the data included in the model, the optimal number of clusters is three (see Figure 4).

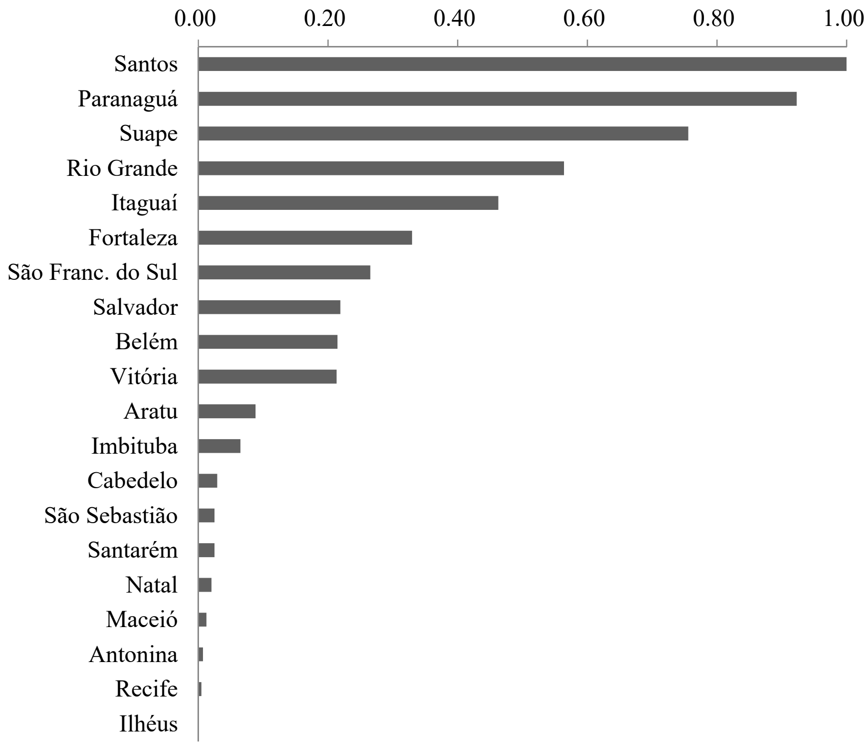

Figure 2. Port ranking by port efficiency score in 2016.

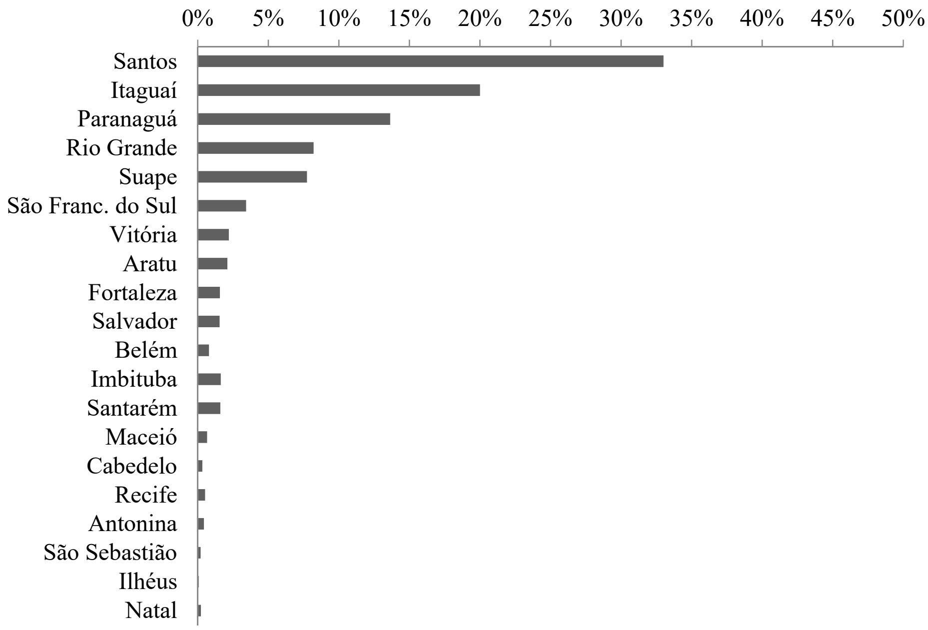

Figure 3. Port ranking by cargo throughput share in 2016.

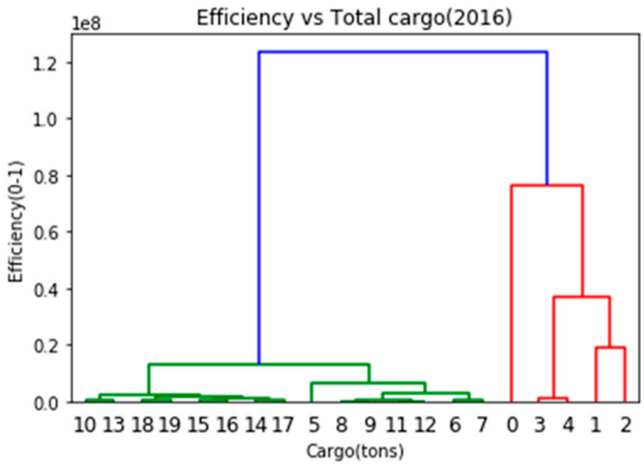

Figure 4. Dendrogram: Port efficiency vs. total cargo throughput (2016).

Clustering groups "elements" based on several characteristics. There are several clustering methods, and each one uses a different approach to group elements. Hierarchical clustering makes each data point a single point cluster. Then, one cluster is created from the two closest data points. This process continues until all the data points are grouped according to the number of clusters determined by the dendrogram (see Figure 5).

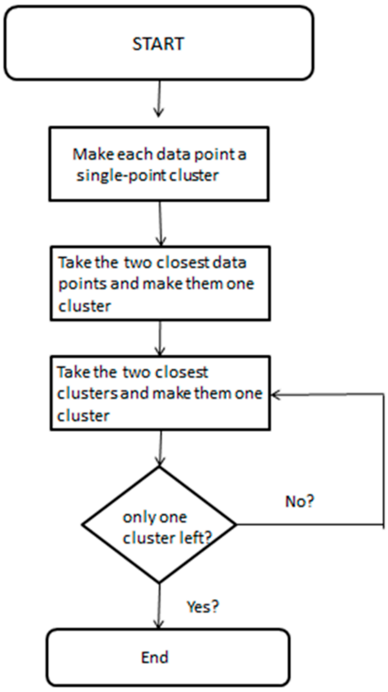

Figure 5. Process flowchart of hierarchical clustering.

The result of the clustering for the efficiency and total cargo variables can be seen in Figure 6. Cluster 1 (blue) represents ports with the highest efficiency and cargo throughput. Cluster 2 (green) can be characterized as "ports of medium dimension" with a high possibility of becoming part of Cluster 1. Finally, Cluster 3 (red), which comprises most of the dots/ports, is composed of ports with low efficiency and lower cargo throughput. Cluster 1 contains Santos port, the port with an efficient score and the highest total cargo throughput. Cluster 2 contains the four ports with the next highest efficiency scores and cargo throughput: Itaguaí, Paranaguá, Suape, and Rio Grande. The 15 ports with lower efficiency and cargo throughput values are in Cluster 3. There is a clear difference between the ports in clusters 1, 2, and 3. In the figure, we can detect the trend that the bigger port shows the more efficient result. However, in case of Cluster 2, three small ports show more efficient score than bigger port.

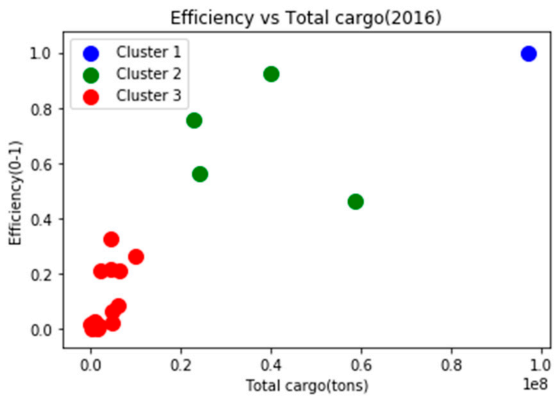

Figure 6. Hierarchy clustering method: Efficiency vs. total cargo throughput (2016).

In the hierarchy clustering, it was observed that the five most efficient ports are grouped in the cluster with the shortest total time of stay, but the same scenario does not occur for waiting time. Most of the high-efficiency ports are spread across the three clusters and present no defined pattern for waiting time or efficiency clustering analysis (see Figure 7). These results indicate that the total time of stay is more important than the wait time. Reducing queue times will require that port processes be optimized and/or that the ports' capacity to receive vessels be increased. Due to the high cost of the second option, the first is more feasible and beneficial to ports; it will reduce costs in the short term.

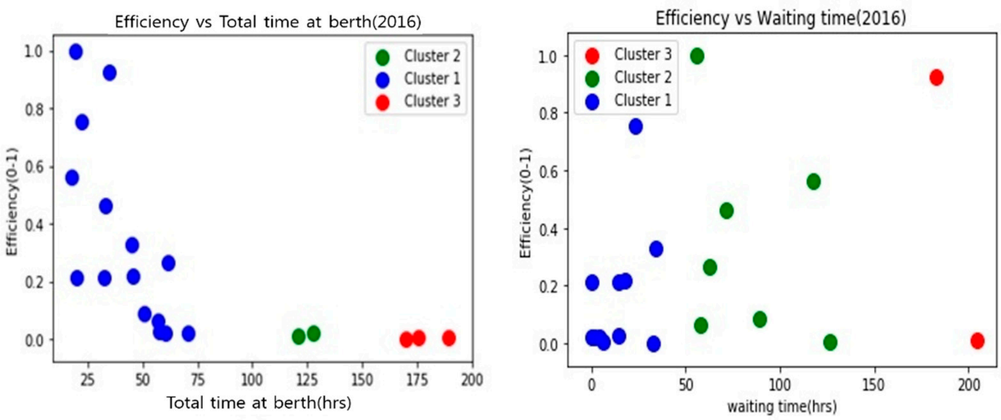

Figure 7. Total time at berth and wait time according to efficiency clustering (2016).

According to the weight scores from the DEA model, two infrastructure variables (length of pier and courtyard) are most important. To analyze whether the most efficient ports have the highest pier length and courtyard values, a clustering method with efficiency scores is conducted (see Figure 8). All inefficient ports are grouped in the cluster based on data reflecting the lowest infrastructure values for both the pier and courtyard. Pier length could be a critical input variable: If the port infrastructure is changed to allow more vessels to be received, waiting time could decrease, and cargo throughput could increase.

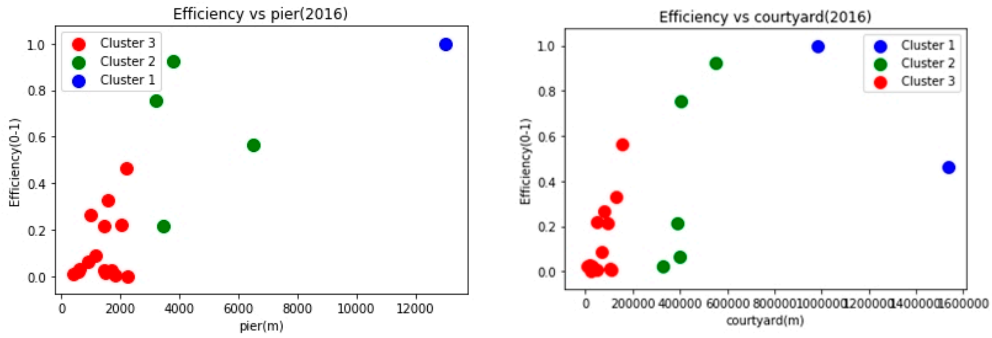

Figure 8. Pier length and courtyard according to efficiency cluster analysis (2016).

Brazilian port authorities need to increase ports' infrastructure to improve their capacity to handle more and larger vessels and to allow them to handle cargo at terminal areas more efficiently. These changes will reduce ship turnaround time and thus improve the productivity and efficiency of the ports. Furthermore, maintaining strict quality management of total time of stay should be a policy priority.

6. Conclusions

This study analyzed the efficiency of 20 Brazilian ports using the BiO-MCDEA method along with six input variables (i.e., length of pier, draught, warehouse, yard, wait time, total time of stay) and one output variable (i.e., total cargo throughput). BiO-MCDEA is an excellent method of measuring efficiency, as it allows significant distinctions to be made between ports. The results show that Santos port is the only efficient port out of the 20 that were examined. The remaining 19, with their differentiated efficiency scores, facilitated the analysis of port efficiency.

Four ports—Paranaguá, Suape, Rio Grande, and Itaguaí—have high efficiency scores; they can be considered intermediate-level ports, and thus have a good potential to become efficient. However, these four ports, along with Santos—the only port with an "efficient" score, represent 25% of the ports studied; the other 75% (15 ports) have very low efficiency scores according to the BiO-MCDEA model.

Through the hierarchical clustering method, 20 ports were classified into three clusters: efficient (one port), intermediate (four ports), and very low efficiency. The five most efficient ports feature the highest cargo throughput in cubic meters. The results show that Brazilian ports need to increase their size to receive additional cargo.

Moreover, despite the long docking wait queues, the dwell time is more important for port efficiency than the wait time. In other words, the total time ships spend in port is the factor that must be reduced for queues to decrease. This can be accomplished by creating more mooring berths, but also by developing more efficient processes. The port of Santos obtained positive efficiency scores over the six years from 2010 to 2016. This result was expected, as Santos is the largest port not only in Brazil but in Latin America

By employing the BiO-MCDEA model, this study enabled a more significant distinction between ports in terms of efficiency. The study also made the first use of the cluster analysis method in conjunction with the BiO-MCDEA to analyze Brazilian ports by clustering groups according to their efficiency levels and input and output variables. Dividing ports into clusters can help Brazil's government and port authorities make decisions on how to improve the infrastructure and processes of Brazilian ports.

Another contribution of this study is its inclusion of two time-related variables (wait time and dwell time). Despite the importance of including time data when measuring port efficiency, no study on Brazilian ports has considered the time factor, even though process efficiency is extremely important for all public Brazilian ports.

Future studies should analyze the relationship among physical port capacity, time-related measures, and performance efficiency using alternative approaches such as tobit regression. Efficiency analysis for both public and private port terminals is required to compare efficiency between the two sectors and to examine how private-sector investment impacts port infrastructure and operations. An efficiency analysis of port terminals for different cargo types, specifically container and commodity cargo, is also required. This study considered all the input and output variables in a single-stage model. This model can measure overall port efficiency as a simple score. Future researchers could provide a more detailed analysis by dividing the model into multiple stages via a network-DEA model, which reflects service and operation processes in sequence and presents three different efficiency scores: overall, service, and operation.

Although we used the bi-objective weighted method of Ghasemi et al. [30] to calculate the MCDEA model, the analyses can be performed in other ways that require fewer computational codes and that have improved discrimination power. We used our method simply because it was better than the GPDEA in terms of mathematical programming and simplicity of formulation. Future researchers should seek metaheuristic solutions for the MCDEA model to improve the procedure used in this study.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Port Infrastructure Data.

Port	Berth Length (m)	Draft (m)	Warehouse (m^2)	Yard (m^2)
Santos	13,013	13.5	499,701	981,603
Itaguaí	2210	19.8	15,242	1,535,109
Paranaguá	3783	12.7	58,260	549,325
Rio Grande	6482	12.8	196,750	155,000
Suape	3200	14.5	20,000	406,000
São Franc. do Sul	975	13.1	8070	79,500
Vitória	3449	11.2	40,000	390,400
Aratu	1,170.8	14.8	30,184	68,400
Fortaleza	1580	13	33,000	131,000
Salvador	2023	13.9	23,300	45,800
Belém	1446	7.3	39,561	92,505
Imbituba	905	14.5	380,004	400,000
Santarém	1700	14	6894	8850
Maceió	1487	10.5	35,200	103,524
Cabedelo	602	12	14,000	18,000
Recife	1826	11.1	29,570	49,410
Antonina	420	16.5	41,415	110,117
São Sebastião	1440	16.9	3000	325,800
Ilhéus	2262	8.5	18,050	20,500
Natal	567	11.5	6600	29,000

Table A2. Time-related Input Data.

Port	Total Time at Berth (h)				Waiting Time before Berthing (h)			
	Min	Average	Max	St Dev	Min	Average	Max	St Dev
Santos	19.0	20.0	23.7	1.7	27.7	51.9	77.7	15.6
Itaguaí	33.1	34.9	38.7	2.1	60.8	108.9	141.1	32.0
Paranaguá	30.9	33.2	36.8	2.1	100.3	197.1	297.4	58.6
Rio Grande	16.9	19.1	21.4	1.7	19.8	51.5	117.8	34.4
Suape	22.5	25.4	31.0	3.4	21.0	25.0	28.4	2.5
São Franc. do Sul	27.7	37.2	61.6	11.5	62.3	91.9	164.0	33.9
Vitória	23.1	26.4	32.7	3.3	12.9	20.6	28.6	5.9
Aratu	50.9	56.6	62.7	4.8	65.1	121.4	234.2	59.8
Fortaleza	33.3	37.3	44.9	3.6	13.9	36.5	66.7	17.9
Salvador	35.7	49.1	57.7	7.1	10.7	32.4	112.2	36.4
Belém	18.0	23.7	29.8	4.5	0.0	0.1	0.4	0.1
Imbituba	44.1	50.9	57.0	4.0	22.2	38.3	57.7	12.3
Santarém	26.9	55.7	127.9	37.2	0.0	0.0	0.0	0.0
Maceió	31.0	51.4	120.9	31.4	24.0	56.9	204.3	65.5
Cabedelo	50.9	58.0	71.7	7.2	11.7	20.3	25.7	5.3
Recife	90.8	127.2	189.5	37.0	4.6	8.3	11.9	2.7
Antonina	101.1	135.4	175.3	29.9	115.8	231.1	409.7	113.0
São Sebastião	57.5	86.8	163.1	38.5	1.1	62.4	152.6	48.4
Ilhéus	84.1	116.5	169.9	33.7	0.1	12.8	43.9	18.0
Natal	48.6	70.2	109.4	19.9	1.1	4.8	11.7	3.7

Table A3. Total Cargo Throughput (tons).

Port	Min	Average	Max	St Dev
Santos	87,838,920.0	94,807,073.7	101,578,071.0	4,763,617.3
Itaguaí	52,765,505.0	58,031,726.9	63,849,720.0	3,257,003.0
Paranaguá	31,107,297.0	39,068,114.0	41,771,840.0	3,802,215.3
Rio Grande	17,072,809.0	20,743,313.6	24,114,921.0	2,607,841.0
Suape	8,885,998.0	14,490,230.1	22,747,980.0	5,091,880.9
São Franc. do Sul	9,532,536.0	11,435,982.6	13,268,335.0	1,644,884.0
Vitória	5,065,851.0	6,649,397.6	8,112,748.0	900,043.3
Aratu	5,188,342.0	5,892,400.6	6,491,715.0	429,229.9
Fortaleza	4,309,971.0	4,725,914.4	5,351,406.0	393,235.2
Salvador	3,424,088.0	3,919,502.1	4,562,312.0	473,892.4
Belém	2,337,665.0	3,002,409.3	3,225,448.0	322,547.3
Imbituba	1,875,760.0	2,899,119.7	4,803,186.0	1,029,040.0
Santarém	1,079,583.0	3,408,698.4	4,975,927.0	1,419,914.8
Maceió	1,963,511.0	2,714,456.7	3,305,545.0	440,004.7
Cabedelo	962,977.0	1,553,090.7	1,907,438.0	368,824.7
Recife	1,410,260.0	1,672,626.6	1,998,676.0	204,150.9
Antonina	235,225.0	1,117,949.1	1,560,210.0	461,416.8
São Sebastião	606,776.0	704,440.6	884,951.0	90,736.8
Ilhéus	195,031.0	349,077.0	506,357.0	124,311.5
Natal	295,891.0	456,680.3	674,788.0	125,835.5

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