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A Frontier Approach to Eco-Efficiency Assessment in the World's Busiest Sea Ports

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Abstract: The maritime economy is at the forefront of unprecedented sustainability challenges. Addressing ecological externalities in port operations supports the decarbonization goals of the United Nations (UN) Climate Action program and port city transition towards resilient and sustainable urban units. This research brings out an empirical assessment of seaport performance from an eco-environmental point of sustainability with a non-parametric analysis. Most common indicators from the cross-sectoral Global Reporting Initiative (GRI) database for 21 world's busiest seaports are used for the analysis. This research integrates four different models with inputs: CO_2 emission, electricity consumption, waste, and water consumption, and; outputs: employee, revenue, and container throughput. Projection pathways are established for inefficient seaports to improve sustainability performance. The analysis shows that the seaports of Qingdao and Cartagena as the most sustainably performing seaports under the selected maritime sustainability indicators. This research supports port managers in understanding the strengths and weaknesses of their operations and helps frame strategic policies toward achieving overall sustainability in the maritime industry across SDG 14 (marine ecosystem) and SDG 13 (Climate mitigation) goals of the 2030 Urban Agenda.

Keywords: eco-efficiency; maritime economy; sustainable development goals; frontier approach; maritime transportation

1. Introduction

Maritime transport forms an integral part of the shipping and marine economy [1], accounting for approximately 80% of the global trade volume [2]. In terms of its unmatched physical capacity and potential to carry freight over long distances at low prices, maritime transport is the epicenter of global trade and network distribution [3]. Besides, maritime trade is expected to increase in the upcoming years [4]. Ports are critical transportation centers that facilitate the flow of types of materials to local markets, industries, and landlocked countries [5]. Ports expedite urban development, and cities offer ports with substantial services and facilities that influence the nature of urban growth [6]. Eco-environmental sustainability, a fundamental concept in port design and management, has become an important part of achieving competitiveness [7]. Maritime transportation is cost-effective when compared to other means of travel except at canals. The low maintenance costs of ships are additive to this benefit. With low energy consumption and minimal manpower needs, ships can transport huge quantities. Shipping, thus an integral part of the marine ecosystem, can deliver very low prices compared with other means for goods and passenger travel [8]. However, it is crucial to examine how well the benefits reaped through the low-cost and lucrative revenues generated can compensate for the associated environmental impacts in this sector.

Increasing knowledge of climate change introduces new obstacles to seaport operations [9]. Ports need to schedule and sustainably manage their activities and development to deal with the climatic consequences and increased relations with their hinterlands [10]. Decarbonizing and bringing sustainability into the global port sector can encourage the achievement of the less-addressed "SDG" of the UN 2030 Agenda, in the maritime industry. Therefore, this research aimed to;

a) Develop models for the assessment of operational efficiency considering the international reporting standards and sustainability guidelines for eco-efficient maritime operations,

b) Build a CCR (Charnes, Cooper, and Rhodes) based Data Envelopment Analysis (DEA) model to assess the eco-efficiency performance of the 21 busiest seaports in the world,

c) Examine recommended reference points to provide a specified evaluation method to improve port sustainability performance, and

d) Provide a framework for port managers to achieve sustainability based on managerial implications as a result of the assessments made.

The notion of "Sustainable Port Production" is based on the concept of "Green Ports", which emphasizes the need for port development to find an equilibrium between economic enhancement, environmental mitigation, and social growth to make sure of its long-run viability [11]. Through its processes and strategies, a green port proactively combines global warming adaptation and mitigation strategies [12].

Port facilities are modernized and retrofitted with technology; otherwise, freight, throughput, and competitive advantage in the industry will be lost. The infrastructure investment and modernization follow the new 'green' criteria for sustainable port management [13]. Eco-efficiency is a managerial-based sustainability assessment technique that can deliver more products and services by consuming less energy and causing less waste and emissions for sustainable port operations [14]. Calculating eco-efficiency is critical to promoting clean development and is used to calculate sustainability in different economic sectors [15]. Eco-efficiency accelerates the delivery of goods and services that are less harmful to the environment. It increases the industry awareness of the environmental and economic advantages of a circular economy and the introduction of environmentally friendly designs with resource-efficient development [16].

The outline of the paper is planned as follows. After the introduction, a literature review on the "GRI" and "DEA" is presented. Following this section, the method part is defined, which covers the process of how Data Envelopment Analysis (DEA) is implemented and how it is used in port sustainability performance comparisons. The data collection section explains how to capture detailed sustainability data from ports all over the world, as well as data for the suggested model variables. The analysis and discussion section provides an outline of the research performed. The research concludes by giving possible recommendations to port managers and decision-makers for long-term sustainable management of the maritime economy. Figure 1 displays the levels, which consist of five distinct points, to demonstrate the flow of the research.

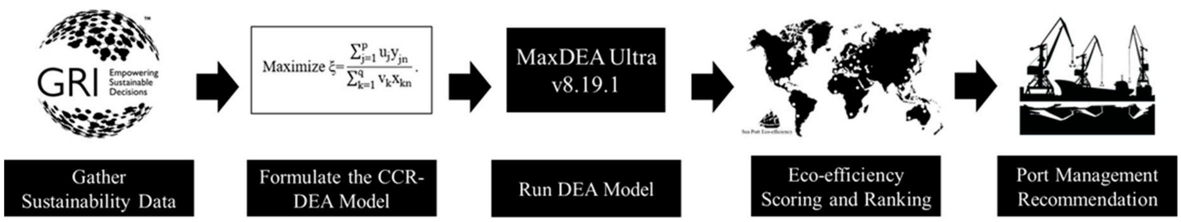

Figure 1. Research flow diagram.

2. Materials and Methods

2.1. Global Reporting Initiative (GRI)

Large-sized corporations now frequently provide sustainability reports as part of their operations [17]. It offers organizations the ability to transparently express their priorities, decisions, and results, to achieve sustainable development and lays down opportunities to address these evolving needs [18]. Orazalin and Mahmood [19] put forward 8 hypotheses based on their research for sustainability reporting. The findings asserted that profitability, leverage, financial capability, firm size, firm age, and external auditing have a beneficial influence on sustainability awareness.

The GRI seeks to facilitate the dissemination and increase the standard of sustainability reporting [20]. Sustainability reporting guidelines for GRI have been created as a means to help organizations report on their ecological, societal, and economic success and improve their liability. GRI is the best-recognized structure for optional reporting by companies and other organizations globally on environmental and social results. Since its establishment in 1999, GRI has been very popular in terms of its adoption rate, comprehensiveness, reputation, and popularity [21]. GRI expects reports on financial, environmental, and social problems to be published regardless of whether this information adversely impacts the corporation [22]. Some ports have adopted voluntary GRI standards to structure their environmental reporting, including environmental performance disclosure requirements that improve sustainability reporting integrity, comparability, and accountability [23].

2.2. Data Envelopment Analysis

The dynamic interaction between multiple inputs (IPs) and outputs (OPs) for each decision-making unit (DMU) in DEA has created new possibilities for its use in situations where other parametric methods have failed [24]. Moreover, DEA as a managerial approach is best suited to assess the sustainable efficiency of business entities [25]. Wang et al. [8] proposed three different DEA models to perform environmental efficiency of 11 different Chinese Ports considering the results of environmental control, non-environmental control, and particular matter emission. Owing to the dynamic arrangement of the interactions between various process IPs and OPs, DEA was used by Eliso-Perico and Ribeiro-da-Silva [26] to evaluate the efficiency of Brazil's 24 seaports between 2010 and 2017. The application of DEA on factors such as facilities, capacity, and logistics services in Brazilian ports resulted in a categorical conclusion shown by the efficiency frontier. Zarbi et al. [27] used panel data to quantify the eco-efficiency of Iran's 5 container ports during the time of sanctions using DEA. A multi-stage non-parametric approach with 10 years long data under efficiency stratification procedures was used for the analysis. The efficiency of Vietnamese ports was also analyzed by Kuo et al. [28] from 2012 to 2016 using DEA. A context-dependent (CD)-DEA model was used for the analysis which was earlier introduced by Seiford and Zhu [29]. The CD-DEA used in the analysis overwhelms the constraints in order to determine the efficiencies of the ports at different evaluation stages. The study analyzed the "returns-to-scale (RTS)" condition of ports in Vietnam. The results showed poor total efficiency of Vietnamese ports due to sheer technical inefficiencies. A significant input surplus, about 55% was identified. Wang et al. [30] conducted three DEA models to assess the performance of environmental efficiency of 11 major Chinese ports. The findings showed that ports in eastern China have higher efficiency and port cooperation can enhance the overall output level but its degree can be decreased with the improvement of particulate matter emission standards.

A variety of non-radial, production-oriented, consolidated DEA models were introduced by Lozano et al. [31] to assess the individual and joint output efficiency thresholds, input slacks, and reassignments of inputs, as well as additional purchases of IPs under capital investment restriction. The model introduced the implementation of possible solutions for the Spanish Port Agency. Without extra capital, the average volume of inefficiency already identified in the system enabled the assessment of possible gross production changes ranging from 24% to 114%. An extra 20% output extension was felt essential when considering input reallocation. As the preferred technique for evaluating the relative performance of container ports, DEA was justified and applied to industrial panel data in several configurations. Likewise to the usage of cross-sectional data, the DEA-CCR and DEA-BCC were adapted to estimate port efficiency [32].

In recent times, research directions have changed from arrangements and policy management perspectives to effective, automated, and sustainable shipping mechanisms in maritime operations. Furthermore, the latest research trends are also found to be linked to supply chain management, sustainability, and environmental monitoring of seaports [33]. In this context, this research proposes multifaceted models to evaluate and relate seaport eco-efficiency under the "sustainable growth" paradigm, accounting for the elevated environmental concerns. In addition, for the proposed models, revenue, load amount, and the overall number of staff are calculated as outputs when maintaining the optimal amount of inputs. In addition, some of the prominent studies published in the area of seaport sustainability are provided as follows. Garg et al. stated that sustainable green port development is essential to deal with environmental issues in China. In this respect, the scholars found the relevant green port development factors such as environment, digitization, automation, and strategy among the six main categories by using the Fuzzy-AHP methodology [34]. Cunha et al. determined sustainability practices for SDGs with content analysis regarding reports published by Brazilian Public Port Authorities between 2017 and 2020. The reports revealed that SDG 8, SDG 11, and SDG 14 are the most preferred factors in the considered period [35]. Spengler et al. analyzed energy consumption differences for both refrigerator and non-refrigerator cargo types to find their impacts on the overall efficiency of container terminals. The results show that output disaggregation revealed different efficiency scores by involving energy inputs in the proposed model [36]. Park et al. developed a performance model to evaluate the operational capability of 9 container terminals at Busan Port using 5 years of data from 2014 to 2019. The analysis part indicated that efficiency in operations is a key qualifier and market aggressiveness affects both the competitiveness and performance of a container terminal positively [37]. Ghiara and Tei used DEA and statistical regression to analyze whether automation guarantees high efficiency. The results indicated that members of certain port families are more important than being technology-driven [38]. Schrobback and Meath aimed to conceptualize and establish a structure for sustainable seaport management by considering the possible improvements in sustainable development plans to acquire wider corporate targets for seaports. The research conducted an observational analysis to find the degree of acceptance by ports in Australia and New Zealand for various sustainable policy components [39].

2.3. Novelty and Research Gap

To date, sustainability studies in the area of seaports have been conducted in specific geographical locations such as Asia and Europe. No research conducted so far has evaluated the eco-efficiency performance of the busiest seaports in the world based on the container traffic volume passing through them. Most of the studies focused on specific regions such as Italy, Malaysia, Canada, and the USA [40]. Despite multiple regions including Southeast Asia, East Asia, and the Mediterranean being considered for evaluation in some studies, a global picture of the marine domain targeting meets the shipping demands and smooth industry operations with the increasing container traffic has not yet been captured into the existing body of knowledge [41]. Studies have targeted the biggest seaports, however, it is not necessarily true that the biggest seaports in the world are the busiest seaports. Busiest seaports often face sustainability challenges based on the increased volume of traffic when compared with the biggest seaports [42]. Thus, container traffic volume as a differentiating factor for sustainability performance assessment is used in this study to capture the true maritime economy picture on the canvas of sustainability.

This research evaluates seaports worldwide with a container throughput value of over 20.1 million TEUs (Twenty-foot equivalent units) of cargo volume passing through them, based on the data available from the reliable GRI database. Also, it compares ports in different regions of the globe based on sustainability standards and determines how significant eco-efficiency is to the regions in terms of marine transportation. Finally, it is aimed to improve seaports' eco-efficiency, ensure sustainability, and provide a quantitative guide for port executives.

2.4. DEA Approach and Data Analysis

DEA evaluates the relative efficiency of uniform DMUs using linear programming models, resulting in efficiency scores ranging from a scale of 0 to 1 [43]. Initially, DEA was developed to approximate the performance of multiple-input/multiple-output units in the "production possibility set (PPS)" and to differentiate the inefficient units from the efficient ones. The DEA model builds a linear utility piecewise frontier to closely encompass all the productive units and measures the inefficiency units based on a "distance-to-frontier" approach [44]. DEA is one of the essential tools to determine efficiency and finds a great deal of application in the area of marine transportation [45].

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DEA was early used by Roll and Hayuth to measure seaport efficiency [46]. Ashar analyzed the seaport efficiency by monitoring the cargo handling performance, where labor, resources, and shipment time were considered as IOs, and throughput was taken as the OP measure [47].

Several basic DEA models exist that change according to the goal and complexity of the analysis to be performed [48]. The CCR and BCC models are the two most popular and conventional variants of DEA models [49]. The CCR model established in 1978 uses continuous returns to scale under optimal conditions [44]. Banker et al. established the "variable returns to scale (VRS)" model to predict efficiencies, where a rise or fall in inputs or outputs does not correspond to a relative change in them (BCC) [49]. The goal of an input-oriented model is to keep generating identical outputs using minimal inputs, while an output-oriented model optimizes the outputs using minimal input quantities [50], [51]. In this study, the CCR approach was chosen to estimate the eco-efficiency performance as it provides the most reliable efficiency assessment in terms of input reduction with accurate outcomes when compared with other possible DEA variants. Thus, the "input-oriented DEA multiplier model" is utilized.

To evaluate a DMU's utility, it is first defined xj and yk as the jth IO and kth OP respectively, where the "virtual input (VI)" and "output (VO)" are specified using the Eq. 1:

$$\mathrm{VI}=\sum_{j=1}^{p} u_j x_j\,;\mathrm{VO}=\sum_{k=1}^{q} v_k y_k\,, \tag{1}$$

Here, p and q represent the number of inputs and outputs for each DMU respectively. ui ≥ 0 and vk ≥ 0 are the assigned weights to the jth and kth IO and OP, respectively for each DMU. The eco-efficiency value is then calculated using Eq. 2:

$$\text{Eco-efficiency}=\xi=\frac{\mathrm{VO}}{\mathrm{VI}}=\frac{\sum_{k=1}^{q} v_k y_k}{\sum_{j=1}^{p} u_j x_j} \tag{2}$$

For each DMU, the weights, ui, and vj are directly allocated using mathematical programming. The DEA model used in this paper is represented by Equations (3)–(5):

Objective Function;

$$\text{Maximize } \xi=\frac{\sum_{j=1}^{p} u_j y_{jn}}{\sum_{k=1}^{q} v_k x_{kn}}. \tag{3}$$

Subject to;

$$\frac{\sum_{j=1}^{S} u_j y_{jn}}{\sum_{i=1}^{M} v_k x_{kn}} \leq 1,\ n=1,2,\ldots,N \tag{4}$$

$$u_j \geq 0,\ v_k \geq 0,\ k=1,2,\ldots q;\ j=1,2,\ldots p \tag{5}$$

where,

X_{jn} = the *j*th input of DMU *n*

Y_{kn} = the *k*th output of DMU *n*

N = cumulative sum of all DMUs

The DEA model, as seen in Equations (3)-(5), relies solely on the appropriate performance measurements (IPs and OPs) selected for the analysis. Table 2 displays the outcomes of the 4 separate DEA models designed to determine the effects of IP variables on the port's eco-efficiency measure.

Table 2. Suggested DEA models with corresponding inputs and outputs.

Model	Inputs	Outputs
Model A	Carbon dioxide emission, electricity consumption, waste, water consumption	Employee
Model B	Carbon dioxide emission, electricity consumption, waste, water consumption	Revenue

Model C	Carbon dioxide emission, electricity consumption, waste, water consumption	Container throughput
Model D	Carbon dioxide emission, electricity consumption, waste, water consumption	Employee Revenue Container throughput

Figure 2 illustrates the standardized GRI reporting procedure adopted for the study, as well as the number of reports disclosed in each phase towards limiting the number of reports for the context of this study.

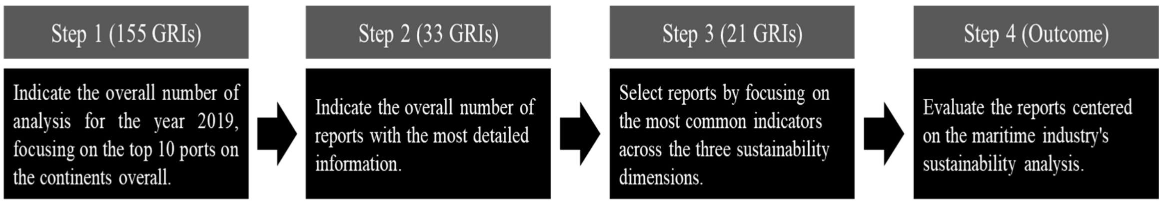

Figure 2. Data collection process using the GRI sustainability database**.**

Step 1 summarizes the findings of the search for 155 GRI reports published in 2019. Only the data corresponding to the top ten ports was extracted, for the regions across Europe, North and Latin America, Asia, Africa, and Australia. Step 2 summarizes the findings of the GRI's filtered search, which only considered the completely released GRI. In this step, 12 sustainability metrics were listed and classified, as seen in Table 3.

Table 3. Sustainability indicators for port efficiency.

Metrics	Economic	Environmental	Social
Revenue	√		
Number of employees	√		
Number of passengers	√		
Assets	√		
CO2		√	
Electricity consumption		√	
Waste		√	
Water consumption		√	
Fuel consumption		√	
Number of accidents			√
Injury rate			√
Number of training			√

The sustainability metrics were analyzed for the year 2019, with a total of 33 separate port sustainability reports. The year 2019 was selected due to the complete availability of data across all the seaport eco-environmental indicators. In step 3, these findings were thoroughly examined and evaluated to identify their extent of coverage in the busiest ports across the world. The number of ports with GRI sustainability, including the most shared metrics, was reduced to 21 seaports as a result of this measure. The descriptive analytics of the sustainability metrics used in this study can be seen in Table 4.

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Table 4. Inferential statistics of the eco-efficiency metrics.

	Emissions	Electricity	Waste	Water	Employees	Revenue	Container throughput
Max	4E+06	3E+09	3E+06	3E+06	9E+03	5.1E+09	2E+07
Min	4E+02	2E+05	4E+03	2E+03	6E+01	1.7E+07	2E+04
Avg	3E+05	2E+08	2E+05	3E+05	2E+03	6.4E+08	5E+06
σ	8E+05	7E+08	5E+05	7E+05	3E+03	1.2E+09	6E+06

3. Results

3.1. Ecoefficiency Performance

The elevated grades of multicollinearity among the inputs and/or outputs are commonly used in DEA as a reason to eliminate certain IPs or OPs. The high intercorrelation in DEA relates to whether two or even more inputs are linearly related to one another. Several approaches exist to assessing multicollinearity in the literature. The sample-based correlation of determination "(R2)" and correlation coefficient also called "Pearson's R" can be used to check multicollinearity [52].

To proceed, the correlation of determination (R2) for each possible IP-OP in the model is evaluated, for which the findings are tabulated in Table 5.

Table 5. Correlation matrix for the selected inputs and outputs.

	Emissions	Electricity	Waste	Water	Employees	Revenue	Throughput
Emissions	**1.00**	0.99	0.08	0.01	0.03	0.90	0.05
Electricity	0.99	**1.00**	0.07	0.01	0.05	0.93	0.14
Waste	0.08	0.07	**1.00**	0.09	0.15	0.13	0.20
Water	0.01	0.01	0.09	**1.00**	0.38	0.20	0.37
Employees	0.03	0.05	0.15	0.38	**1.00**	0.26	0.71
Revenue	0.90	0.93	0.13	0.20	0.26	**1.00**	0.47
Throughput	0.05	0.14	0.20	0.37	0.71	0.47	**1.00**

The findings indicate a weak correlation for the set of indicators chosen, with ranges from $0.01 \leq R^2 \leq 0.99$. The most correlated pair of variables are electricity and emissions (R2 = 0.99), while the least correlated pairs include water and emission ($R^2 = 0.01$). No IPs or OPs were excluded in this study due to there being no proof of multicollinearity among them.

Using the relevant IPs and OPs, the ξ values of the 21 busiest seaports are measured in the world under all 4 DEA models. Figure 3a shows the eco-efficiency scores and the ranking of the seaports measured using Model A for each of the 21 ports under study. Under Model A, the port of Ravenna is placed at the bottom of the ranking list with an efficiency value of ξ = 0.0126. While, with a score of 1, the ports of Qingdao (ξ = 1.00), Valencia (ξ = 1.00), and Cartagena (ξ = 1.00) topped the list of the most eco-efficient seaports. Model B's ξ values are depicted in Figure 3b. The Qingdao port and Valencia port's ξ performance remained stable in both Models A and B. While, the outcomes of Model A and Model B were evaluated, it was clear that the Tianjin and Melbourne ports had dropped from the high to the low ranking zone. Under this category, the ports of Valparaiso, Hong Kong, and Brisbane also topped the list of the most eco-environmentally performing seaports for the year selected.

The values calculated using Model C can be seen in Figure 3c. According to the findings, the Port of San Diego is the least efficient port (ξ = 0.002). Similar to the performance showcased in Model A and Model B, the port of Cartagena and Qingdao retained their position as the most efficient seaport along with other seaports like Hong Kong, Valencia, Melbourne, and Valparaiso. The ξ values calculated using Model D are shown in Figure 3d along with the ranking of each seaport. The findings of Model D show that many ports, including Barcelona, and Arica, have significantly improved their sustainability performance. It can be seen that under this model; Barcelona, Valencia, Qingdao, Hong

Kong, Valparaiso, Arica, Cartagena, Melbourne, and Brisbane are the seaports that are efficiently performing.

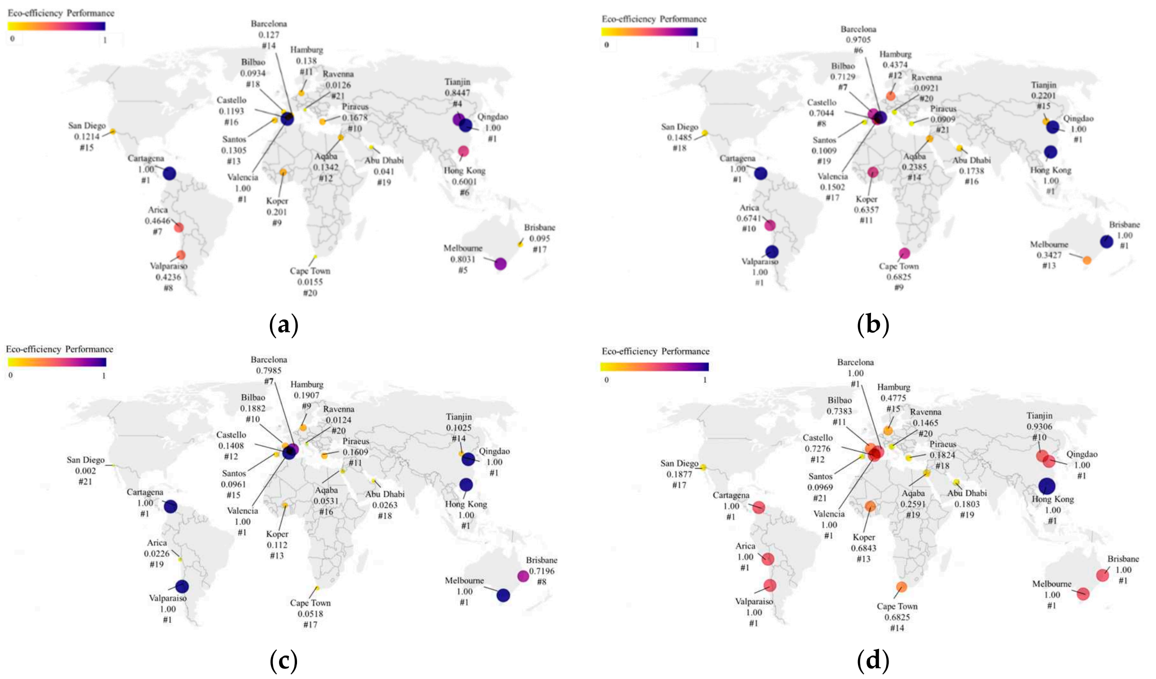

Figure 3. Eco-efficiency results for the 21 seaports under a) Model A; b) Model B; c) Model C; d) Model D.

3.2. Efficiency Performance Grouping

This section focuses on categorizing DMUs based on their efficiency score level. The “Quartiles” method is used to divide a data series into 4 equal interval categories to create 3 threshold points. These groups are labeled as “Bad”, “Good”, “Very good”, and “Excellent”. The effect of using OPs on productivity performance assessment will be determined by categorizing them. However, once the groups' thresholds are defined, each DMU is allocated to one of them based on its ξ.

The color on a gradient for each value across all the models is shown in Figure 4. The color code's accuracy indicates that a port's efficiency output has been consistent over the four models observed. The findings indicate that the ports of Cartagena and Qingdao performed "Excellently" in both of the models conducted. Abu Dhabi, Aqaba, Piraeus, Ravenna, San Diego, and Santos showcase a relatively “Bad” performance under all the models. Furthermore, it can be seen that the seaports of Barcelona, Hong Kong, Melbourne, Valencia, and Valparaiso perform “Very good” in terms of addressing eco-environmental sustainability.

Ports	Model A	Model B	Model C	Model D
Abu Dhabi	1	1	1	1
Aqaba	1	2	1	2
Arica	2	3	1	4
Barcelona	1	4	4	4
Bilbao	1	3	1	3
Brisbane	1	4	3	4
Cape Town	1	3	1	3
Cartagena	4	4	4	4
Castello	1	3	1	3
Hamburg	1	2	1	2

Hong Kong	3	4	4	4
Koper	1	3	1	3
Melbourne	4	2	4	4
Piraeus	1	1	1	1
Qingdao	4	4	4	4
Ravenna	1	1	1	1
San Diego	1	1	1	1
Santos	1	1	1	1
Tianjin	4	1	1	4
Valencia	4	1	4	4
Valparaiso	2	4	4	4

Color scheme

	Bad		Good		Very Good		Excellent

Figure 4. Grouped performance score across DEA models.

3.3. Variability Estimation of DEA Models

The Kruskal-Wallis H test determines whether the different DEA models have the same mean ξ score or not. The non-parametric statistical test shows whether two or more samples come out of the same distribution [52]. This study examined the null hypothesis H0 = μξ (A) = μξ (B) = μξ (C) = μξ(D) to the alternative hypothesis H1 = μξ (A) = μξ (B) ≠ μξ (C) = μξ (D); where μξ (i) represents the mean ξ score corresponding to each DEA model. The test statistic "(K)" is determined as follows:

$$K=\frac{\sum_{\text{all } i}\left(\bar{Z}_i-\bar{Z}\right)(N-1)}{\sum_{\text{all } i}\sum_{j=1}^{nj}\left(Z_{ij}-\bar{Z}\right)^2} \quad ; \quad i=1,2,3,4 \tag{6}$$

where;

nj = no. of DMUs concerning the ith model

N = total amount of DMUs

Z_{ij} = rank of the jth observation concerning the ith model

$\bar{Z}_i$ = average rank considering the ith model

$\bar{Z}$ = average rank concerning all of the models

The Kruskal-Wallis test statistic is compared to a 0.05 significance level to account for significant differences in the α diversity. The p-value is then compared to the K. If the p-value > α, the K statistic is insignificant (accept H0). In other words, there seems to be no sign of variations in the "mean ξ score" of the considered DEA models in this study. However, if the condition of p-value ≤"α" is held, there is ample proof to demonstrate that the "mean ξ score" across each varies significantly from one another (accept HA). The test statistics K and p-value are determined to be 32.22 and 0.00001, accordingly. The results reveal at least one or more of the DEA models dominate the other, sufficient to reject H0.

A pairwise comparison of the test statistics is conducted to understand how the choice of inputs and outputs influences the ξ scores across each DEA model. The pairwise comparison finds the DEA models that have relatively identical ξ scores. The possible combinations are determined using C_r^n = C_2^4; for n = 4 and r = 2, n indicates the number of DEA models and r demonstrates the number of subsets. The outcomes of the pairwise comparison for a significance level of 0.05 can be seen in Table 6. The decision outcome for each pair of models compared can be seen in the table. The findings in Table 4 reveal insignificant differences in the ξ scores of Models A and B. The results are however the same when compared for Model C and D. Eventually, the ξ scores reveal four DEA models with different means. The decision-makers can frame guidelines for potential sustainability evaluation and growth when such findings are made. The findings, however, show that the DEA models are

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vulnerable to variations in the IPs and OPs. To improve the model outcome, begin by choosing the most appropriate IPs and OPs as a first step. Variable selection approaches can be utilized to identify the most suitable set of IPs and OPs prior to running the DEA analysis. Such selection approaches would allow for a reduction in both dimensionality and effects on high correlation. Applications of variable selection in the field of sustainability are also included in the research conducted by Park et al. and Abdella et al. [53], [54].

Table 6. Pairwise assessment of the DEA models' ξ results.

Test models	K-stat	P-value	Outcome	
			Significant	Insignificant
Model A vs. Model B	12.214	0.101		√
Model A vs. Model C	19.429	0.003	√	
Model A vs. Model D	21.452	0.004	√	
Model B vs. Model C	23.786	0.000	√	
Model B vs. Model D	9.238	0.215		√
Model C vs. Model D	19.024	0.011	√	

3.4. Projection Level Analysis

A projection-level analysis is carried out for all 4 different models discussed in this study. To project the inefficient ports to 100% efficiency, the planned percentage decrease illustrates to what extent each of the environmental impact indicators can be decreased. The analysis helps in taking necessary actions to boost the sustainability performance of each underperforming port. Figure 5 shows the projection pathways to improve the sustainability performance of each seaport across the selected environmental indicators. Figure 5a depicts the projection pathways for model A to consider in increasing the port efficiency performance. According to the analysis, Ravenna Port is the least efficient of all the 21 seaports, with an efficiency score of 0.0126. The reference is set to the Valencia seaport, indicating that the frontier port should be examined for the desired levels of efficiency improvement. The weight determined for Valencia Port to be computed is 0.024. Therefore, each input parameter of the Valencia port must be multiplied by the specified weight to help the Ravenna port become an efficient unit.

Table A1 in Appendix A shows the proposed values designating that the port should decrease emissions by 98.744%, electricity consumption by 98.888%, waste by 99.999%, and eventually water consumption by 99.803%, to boost the port's sustainability performance.

In addition, as the environmental variables decline due to possible strategic improvements by the port management, the output variable (the revenue) in model B will rise to enhance sustainability performance. According to the DEA results, Piraeus port is the seaport with the lowest efficiency value (ξ = 0.0909), and its benchmark includes; Hong Kong port and Valparaiso port. The benchmark ports are assigned weights of 0.122 and 0.033, respectively. Multiplying the input variables of Hong Kong port and Valparaiso port with the assigned weights would assist Piraeus port in being a more efficient unit (Table A2). Furthermore, with a score of 0.002, the San Diego port appears to be the least efficient port, with Cartagena and Valparaiso ports included in the reference set. Weights of 0.008 and 0.051 should be multiplied by the inputs of Cartagena and Valparaiso ports respectively to achieve the efficiency targets (Table A3). Moreover, the port of San Diego should decrease emissions by 99.976%, electricity consumption by 99.805%, waste by 99.894%, and water consumption by 99.805% in order to improve its environmental efficiency from a resource usage standpoint (Figure 5c).

Finally, model D integrates all the output and input metrics into a single model to compare them with one another. With a 0.0969 performance score for this model, the DEA analysis indicates Santos Port as the least efficient unit. This port is benchmarked to the ports of Valencia, Cartagena, and Valparaiso, indicating that these three frontier ports should think about reaching the prescribed target levels. Benchmark ports are given weights of 0.361, 0.007, and 4.51, respectively. In addition, to achieve a satisfactory level of sustainability performance, this port should reduce the input

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variables by an average of 89.98 (Table A4). Figure 5d shows the proposed grades of each input variable in summary. Ports can improve their sustainability performance and become the best sustainable unit in their industry by applying the above models to their operations and implementing the recommendations for improving the efficiency of each variable.

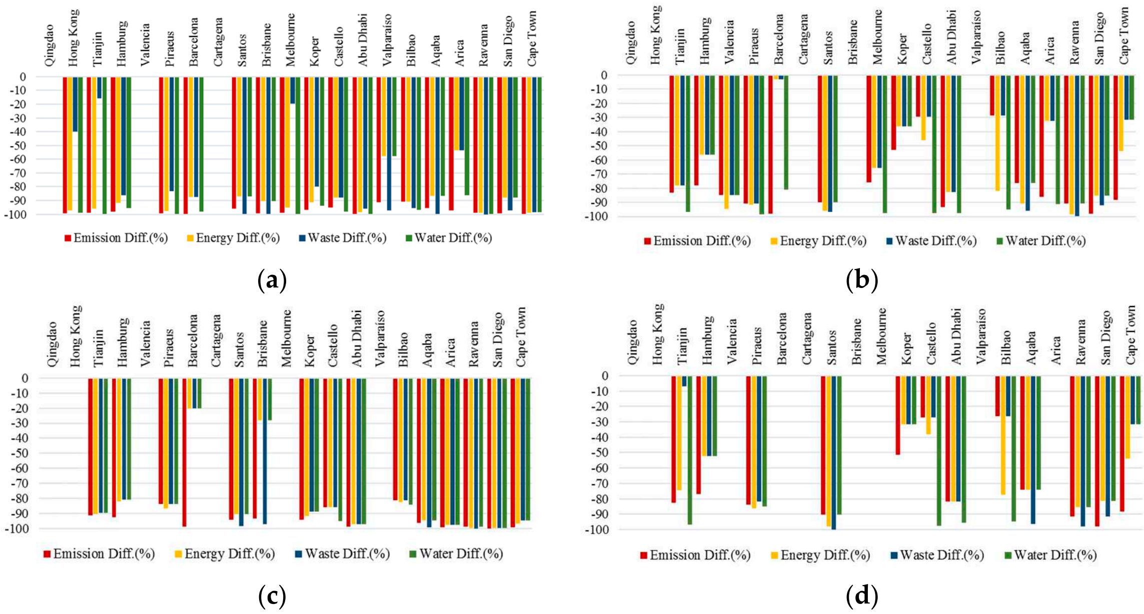

Figure 5. Projection pathways based on the percentage of environmental evaluation criteria (a) Model A (b) Model B (c) Model C (d) Model D.

4. Discussion

The frontier approach discussed in this research is a method to empirically assess the port performance from an eco-environmental point of sustainability. All the information was gathered from reliable sources and utilized in the DEA approach to assessing the relative sustainability of each of the 21 world's busiest seaports. The outcomes were observed and recorded. The study used 4 DEA models; each model showed variable relative efficiency in terms of possible variations in the choice of output. Furthermore, projections were established for every port in terms of what they should improve and to what extent to enhance their sustainability performance. Most importantly, the authors encourage all relevant ports to use the data and knowledge gathered in this study to enhance their port efficiency by improving the environmental variables discussed.

The eco-environmental data utilized in this research to assess the sustainability level of seaports were restricted to a single year due to several data availability constraints. Consequently, it can be gathered more sustainability outcomes from existing Permanent International Association of Navigation Congresses (PIANC) reports and the Environmental Ship Index (ESI) to make these outcomes more efficient and appropriate for businesses to be satisfied with using them. Also, the sustainability data collected from GRI reports and presented in this study were from 2019. The authors suggest using longitudinal data to evaluate sustainability performance over time. Changes in productivity over the years can often be insightful to port managers and decision-makers in bringing effective strategies to reduce the ecological burden. This helps authorities to understand whether the introduction of sustainability initiatives such as EcoPorts, International Association of Navigation Congresses (IAPH) Cruise project, Global Maritime Energy Efficiency Partnerships Project (GloMEEP) project, Noise Exploration Program to Understand Noise Emitted by Seagoing Ships (NEPTUNES) project and many more initiatives to promote port sustainability are bringing true results or not in practice. For the same, the authors recommend using the Malmquist DEA model. A recommendation to improve the analysis is to increase the consistency and applicability of the approach presented by expanding the evaluation with more data and the number of seaports. The total number of ports considered in the study was limited to 21 ports due to the limited data availability. Most of the datasets were often incomplete when attempting to collect data for more indicators and seaports. Furthermore, it was also hard to access up-to-date data that were not involved in the port's sustainability reports. Therefore, the authors propose that each port authority use the most recent and reliable GRI version and that the entire dataset for environmental, economic, social, and governance-related metrics be made open and public. When a large number of data forms part of an eco-efficiency analysis, the authors recommend variable selection using techniques such as "Principal Compound Analysis (PCA)" and "Least Absolute Shrinkage and Selector Operator (LASSO)" to reduce the dimensional space and then proceed with DEA to rule out bias in the efficiency results.

In the face of global energy shortage and ecological deterioration, the major strategic direction for the marine industry has shifted to acquiring sustainable development in their operations [55]. Thousands of people work in the maritime sector, which transports goods across international boundaries. Therefore, managers and department employees must be careful about managing resources correctly and wisely. Sustainable and efficient port management is critical for reducing natural resource usage and mitigating the environmental impacts of the service system as a whole. When assessing the eco-efficiency of seaports, new methodologies should be developed and implemented. These methodologies can help ports determine how to cope with emerging technologies, taking into account both environmental and economic factors. Managers should suggest policies that contribute to maintaining available resources and generating new ones in this sense to be able to achieve extending sustainability results. Also, managers should be mindful of the importance of controlling human resources, which is the most valuable resource an organization can acquire.

The effect of Industry 4.0 has started to revolutionize the whole seaport and maritime sector, and the concept of "Port 4.0" has become a paradigm that has sought much attention recently [56]. Although with the pros, the digital transition process and the expansion of Industry 4.0 into the maritime transportation industry will carry with it plenty of environmental consequences for the seaport and harbor economy. As a result, the implementation of new devices and approaches will harm the ports' environmental sustainability. Furthermore, landfill demand will become an emerging topic as a result of new competencies required, while recycling will become obsolete which needs to be addressed using circular economy practices.

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Appendix A

Table A1. Benchmark array and possible projection levels for Port Ravenna in Model A.

Variables	Port of Ravenna best-level	Benchmark unit	Average projection (%)
CO_2 emission (ton)	84.856	Port of Valencia	99.35
Total electricity consumption (kWh)	293471.55		
Waste generation (ton)	33.595		
Water use (m^3)	132.306		

Table A2. Benchmark array and possible projection levels for Port of Piraeus in Model B.

Variables	Port of Piraeus best-level	Benchmark unit	Average projection (%)
CO_2 emission (ton)	5856.47	Port of Hong Kong Port of Valparaiso	94.96
Total electricity consumption (kWh)	5947909.8		
Waste generation (ton)	98.748		
Water use (m^3)	8766.56		

Table A3. Benchmark array and possible projection levels for Port of San Diego in Model C.

Variables	Port of San Diego best-level	Benchmark unit	Average projection (%)
CO_2 emission (ton)	21.643	Port of Cartagena, Port of Valparaiso	99.86
Total electricity consumption (kWh)	13999.28		
Waste generation (ton)	155.588		
Water use (m^3)	913.982		

Table A4. Benchmark array and possible projection levels for Port of Santos in Model D.

Variables	Port of Santos best-level	Benchmark unit	Average projection (%)
CO_2 emission (ton)	2886.59	Port of Valencia, Port of Cartagena, Port of Valparaiso	89.98
Total electricity consumption (kWh)	5446157.41		
Waste generation (ton)	9530.97		
Water use (m^3)	10867.8		

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