Assessing the Eco-Efficiency of Coastal Shipping in Brazil with the DDF Malmquist Model

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Abstract. Brazil's coastal shipping represents a potentially sustainable transport alternative, but adoption remains limited. This research addresses this gap by analyzing the sustainable and operational performance of Brazilian coastal shipping using the DDF Malmquist model. The study proposes a novel approach integrating the Directional Distance Function (DDF) and Malmquist index to evaluate efficiency, productivity, and eco-efficiency. Applied to a shipping company, the approach demonstrates step-by-step implementation. Ships serve as decision-making units, with greenhouse gas emissions a key output. The DDF model measures efficiency, followed by the DDF Malmquist model to assess productivity over time. The final phase proposes performance improvement guidelines. The findings showcase the DDF Malmquist model's ability to provide a nuanced sustainability perspective, enabling in-depth eco-efficiency analyses of ships. Results reveal superior eco-efficiency for the company's own vessels versus partners, possibly due to an observed revenue-emissions relationship. This study theoretically contributes by addressing Brazil's maritime sector eco-efficiency and productivity assessment gap using the DDF Malmquist model. It facilitates comparative ship analysis over time, unifying eco-efficiency and productivity evaluations while considering desirable and undesirable outputs. The study highlights Brazilian coastal shipping's sustainability potential and provides valuable insights to improve its performance.

Keywords: Coastal shipping, Eco-efficiency, DDF Malmquist.

1 Introduction

Coastal shipping, as a vital logistical option for efficiently transporting goods across Brazil, offers a swift, cost-effective, and environmentally friendly alternative for businesses. With more than 85% of the population residing within 400 kilometers of the coastline, the expansion of coastal shipping not only aids transport companies but also generates employment in the surrounding communities [1]. The advantages of coastal shipping extend beyond low risks of cargo theft and damage, encompassing environmental benefits and direct/indirect cost savings [2]. In the global context, maritime emissions contribute a mere 2.89% to anthropogenic greenhouse gas emissions, while road networks emit approximately 71% of total transport-related emissions [3].

Embracing the Sustainable Development Goals (SDGs) outlined in the UN's Agenda 2030, particularly the imperative to reduce maritime emissions by 70% before 2050, places the Brazilian maritime industry in a strategic position for growth [4] Companies increasingly adopt Environmental, Social, and Corporate Governance (ESG) metrics to evaluate their Corporate Social Responsibility (CSR) activities, underscoring the importance of a holistic approach that considers financial, social, political, and environmental actions[5].

In this context, there is still a need to address coastal shipping efficiency from a sustainable perspective, examining its potential economic and environmental gains[6].

While various performance analysis methods exist in the literature, including stochastic frontier analysis (SFA), Corrected Median Absolute Deviation (CMAD), Modified Ordinary Least Square (MOLS), and Thick Frontier Approach (TFA), a significant research gap exists in applying these methods to evaluate the sustainability of ships operating in Brazilian coastal shipping [7].

In addition to these approaches, there are non-parametric methods, such as Data Envelopment Analysis (DEA), which consider the existence of multiple inputs that estimate economic and environmental impacts for more efficient operations that support decision-makers in analyzing investment policies [8–10]. Therefore, the best eco-efficiency of the transportation operation chain should be studied to better use transportation modes [8, 11].

DEA, extensively utilized across various sectors, facilitates the measurement of economic and environmental impacts for more efficient operations, aiding decision-makers in investment policy analysis [8]. While DEA has been extensively applied in assessing operational efficiencies in maritime logistics [12], its usage in evaluating the efficiency of ships engaged in coastal shipping, specifically from a sustainable tripod perspective (economic, social, and environmental), is notably absent in the current literature [13]. With the primary goal of addressing this gap, our research poses fundamental questions: Which ships demonstrate superior eco-efficiency among the observed Decision-Making Units (DMUs)? What are the key inputs or outputs influencing less efficient DMUs? How can a scenario be formulated to adjust and balance the studied ships more efficiently?

This study proposes a new approach to evaluate the eco-efficiency of coastal shipping operations in Brazil, using DEA, DDF, and the Malmquist index. It considers economic, social, and environmental aspects, including greenhouse gas emissions. The research provides valuable insights into the eco-efficiency of Brazilian coastal shipping operations, helping decision-makers enhance maritime operations while reducing environmental impacts. Both desirable and undesirable outputs offer a comprehensive and analytical study, generating eco-efficient indicators for decision-makers.

This research is divided into five sections. The first section is an introduction, followed by a theoretical foundation on classical DEA models in the context of sustainability and coastal shipping in Section 2. Section 3 outlines the efficiency measurement methodology, while Section 4 details the data and decision-making units used in the DEA analysis. This section also discusses the results, elucidating the causes and consequences. Finally, Section 5 concludes and suggests areas for future research. It evaluates the extent to which the initial objectives have been achieved and the contribution of this work to the existing literature.

2 Theoretical background

2.1 DEA, DDF and Malmquist Index

Data Envelopment Analysis (DEA) is a non-parametric approach developed by [14] to assess the relative efficiency of DMUs through linear programming. It involves relating input and output variables to calculate the efficiency of various entities, such as hospitals, companies, or countries. The DEA model requires homogeneity among DMUs to ensure meaningful comparisons [15]. In the DEA framework, inputs and outputs serve as benchmarks, with DMUs on the efficiency frontier considered efficient and those outside deemed inefficient. Inefficient DMUs aim to improve by adjusting their data based on benchmark DMUs study [16]. The primary goal of DEA is efficiency enhancement, allowing for a comparative analysis of productive units and identifying areas for improvement.

DEA models come in different orientations: output-oriented models seek efficiency by maximizing outputs while keeping inputs constant, and input-oriented models aim to reach the efficiency frontier by minimizing inputs while keeping outputs constant. Additionally, non-oriented models allow both inputs and outputs adjustments [17]. Two classic DEA models widely used are the Charnes, Cooper, and Rhodes (CCR) model, also known as the Constant Returns of Scale (CRS), which assumes proportional changes in inputs lead to proportional changes in outputs, and the model can be linearized and solved as a linear programming problem [14]; and the Banker, Charnes, and Cooper (BCC) model, also known as Variable Returns to Scale (VRS), which is considered an extension of CCR, and introduces the idea of convexity, providing a tighter envelope of data [18]. A DMU's efficiency (Effo) is calculated using weighted inputs and outputs, where weights are assigned to favor the decision-making unit's strengths.

The ADD approach is the incorporation of undesirable outputs into desirable outputs with the signal changed. This approach uses the same principle as INP, which incorporates the undesirable outputs as inputs, but in this case uses a different sign [19]. The INP allows undesirable outputs to be included in the DEA model, used as inputs to the problem, and applied in the CCR and BCC models. TRβ, on the other hand, uses the method of translating values, adding a positive scalar, βi, to the ADD approach, which is large, enabling positive results for the decision-making units. This approach requires the model to be translation invariant, so the CCR model cannot be used in this case as it is a translation variant, unlike the BCC model [20]. Finally, the Multiplicative Inverse (MLT) approach is used with the inverse of the undesirable output (1/u), maximizing the output and keeping it as an output [21]. This approach cannot be used when the undesirable output is zero.

The MLT approach, chosen for its suitability in the given context, maximizes undesirable outputs and is particularly effective when outputs are non-zero. This method accommodates the nuances of specific cases, providing a more efficient and direct calculation.

The conventional DEA model uses strong disposability, as it allows any output to be produced at no cost. However, in the case of undesirable outputs, it is necessary to use weak disposability since this implies expensive, undesirable outputs, which can only be reduced when desirable outputs are also reduced [22].

In this context, the Directional Distance Function (DDF) model has recently been used in cases where efficiency is measured by increasing desirable outputs while decreasing undesirable outputs and reducing inputs, where this is done by means of a direction vector. Luenberger's scarcity function [23] is used in this approach to provide performance measures that respond directly to reductions in undesirable outputs. To evaluate inefficiency, the DDF model can be used, where the function (1) represents it:

$$\vec{D}\mathrm{T}(x, y, u; gy, gu) = \mathrm{MAX}\ \{\beta: (y + \beta gy, u - \beta gu \in \mathrm{T}\} \quad (1)$$

In equation (4), $\vec{D}$T is the distance function in technology T. Variables y and u are desirable and undesirable, respectively. The direction vector g for the desirable variable is gy, and for the undesirable, it is gu. The proportion that seeks to increase desirable output and reduce undesirable output is symbolized by the inefficiency index β. Using the DDF model with linear programming to calculate the eco-efficiency of a DMU m by CRS and weak disposability of undesirable outputs by [24], the function (2) is found:

$$\mathrm{Max}\ \beta m \quad (2)$$

$$\text{Subject to:}$$
$$\sum_{n=1}^{N} z_n\, x_{in} \leq x_{im},\ i = 1, 2,\dots,I$$
$$\sum_{n=1}^{N} z_n\, y_{jn} \geq y_{jm}\ (1 + \beta m),\ j = 1, 2,\dots,J$$
$$\sum_{n=1}^{N} z_n\, u_{kn} = u_{km}\ (1 + \beta m),\ k = 1, 2,\dots,K$$
$$z_n \geq 0,\ n = 1,2,\dots,N$$

In expression (2), we have: the intensity variables as z_n; x_{in} is the i-th input of the n-th DMU; y_{jn} is represented by the j-th desirable output of the n-th DMU; while x_{im} is the i-th input of the m-th DMU; y_{jm} is the j-th desirable output of the m-th DMU; u_{kn} is the k-th undesirable output of the n-th DMU; the k-th undesirable output of the m-th DMU is u_{km}.

A score of zero indicates an efficient DMU, while a positive score is always inefficient. The direction vector of g will be (y, -u), and βm must be greater than or equal to 0 and less than or equal to 1. To obtain the eco-efficiency score of the DDF model (ẚm), ẚm = 1 – βm. Where ẚm is also in the range 0 to 1. Thus, the DDF method is a flexible approach and uses steering to expand desirable output and reduce undesirable output. This model allows efficiency to be assessed by a vector of observed point directions. It is very simple and easy to put into practice.

In addition, the Malmquist DDF model is a way of comparing different decision-making units in the same period and the changes in the production index in different periods. It stands out for not needing a definition of the function's behavior, such as minimizing costs and maximizing revenues. Productivity changes can be broken down by identifying the nature of the change [25].

The indicators of the partial productivity factor (PPF) indicate the yield of one factor at a time, while the second indicator is the total productivity factor (TPF), which shows how much product can be produced with all the inputs used.

The TPF measure in equation (3) indicates a single product (y) and a single input (x) in two periods, t and t+1.

$$\mathrm{TPF} = \frac{y^{t+1}/x^{t+1}}{y^{t}/x^{t}} \tag{3}$$

Looking at function (4), it is possible to analyze this case for the distance function relative to the technology of period t (D_P^t). This shows the division of the distance to the production frontier with inputs and consumption in period t by the same inputs and consumption in period t+1:

$$\mathrm{TPF} = \frac{D_P^t(x^{t+1}, y^{t+1})}{D_P^t(x^t, y^t)} \tag{4}$$

This index can also be called the Malmquist productivity index, which is represented by equation (5):

$$M_P^t\,(x^t, y^t, x^{t+1}, y^{t+1}) = \frac{D_P^t(x^{t+1}, y^{t+1})}{D_P^t(x^t, y^t)} \tag{5}$$

In addition, Malmquist indices use a similar idea to the Fisher index, which uses the geometric mean of the Paasche index and the Lapeyres index to show the largest and smallest jumps to the true index [26]. Therefore, equation (6) defines the Malmquist Productivity index Production Orientation (Mp), with the geometric mean of periods t and t+1.

$$M_P^t\,(x^t, y^t, x^{t+1}, y^{t+1}) = \left(\frac{D_P^t(x^{t+1}, y^{t+1})}{D_P^t(x^t, y^t)} \text{ x } \frac{D_P^{t+1}(x^{t+1}, y^{t+1})}{D_P^{t+1}(x^t, y^t)}\right) \tag{6}$$

With the application of the Malmquist index seen in equation (6), when directed to the DDF model, it is applied in expression (7):

$$M_P^t\,(x^t, y^t, x^{t+1}, y^{t+1}) = \sqrt{\left(\frac{D_P^t(x^{t+1}, y^{t+1})}{D_P^t(x^t, y^t)} \text{ x } \frac{D_P^{t+1}(x^{t+1}, y^{t+1})}{D_P^{t+1}(x^t, y^t)}\right)} \tag{7}$$

Following equation (7), it is possible to separate a technical change from a change in technical efficiency, as shown in equation (8):

$$M_P^t(x^t, y^t, x^{t+1}, y^{t+1}) = \left(\frac{D_P^{t+1}(x^{t+1}, y^{t+1})}{D_P^t(x^t, y^t)}\right) x \sqrt{\left(\frac{D_P^t(x^{t+1}, y^{t+1})}{D_P^t(x^{t+1}, y^{t+1})} \text{ x } \frac{D_P^t(x^t, y^t)}{D_P^{t+1}(x^t, y^t)}\right)} \quad (8)$$

Where expression (9) refers to the change in efficiency between periods t and t+1:

$$\text{EFFCH} = \left(\frac{D_P^{t+1}(x^{t+1}, y^{t+1})}{D_P^t(x^t, y^t)}\right) \quad (9)$$

Expression (10), on the other hand, deals with the best practices used in periods t and t+1, where the geometric mean between the movements in these periods refers to the change in technology:

$$\text{TECH} = \sqrt{\left(\frac{D_P^t(x^{t+1}, y^{t+1})}{D_P^t(x^{t+1}, y^{t+1})} \text{ x } \frac{D_P^t(x^t, y^t)}{D_P^{t+1}(x^t, y^t)}\right)} \quad (10)$$

Thus, looking at the EFFCH and TECH formulas, it is clear that productivity and the components measured are inversely proportional since an improvement in one can lead to a decline in the other. The calculation of the technical efficiency index considers constant returns to scale in this process of calculating distance functions.

2.2 Related works in sustainability and transport

DEA serves as a tool for assessing performance across industries, with a focus on sustainability. New models have been developed over the years to enhance data efficiency in applying DEA to sustainability. For example, [27] proposed an alternative approach using both desirable and undesirable outputs, employing the Malmquist CO2 Emission Performance Index for time series data analysis.

More recently, DEA models have incorporated a new multiplier restriction method. Studies are increasingly focused on minimizing undesirable outputs [28]. DEA also serves as a model for measuring transportation system efficiency, which is crucial for countries like Brazil. Approaches include assessing sustainability and operational interactivity between cities and ports [29], revenue and cost benchmarking to mitigate operational failures, and maximizing fuel efficiency while minimizing emissions [30].

The Malmquist index with DEA has also been utilized to assess freight transport productivity over time [31]. In summary, various DEA models using financial, operational, and sustainability indicators have been applied across transport sectors for efficiency analysis.

3 Methodology

This section presents the phases of the empirical study process and the models applied in each of the cases, with their characteristics and advantages for the final objective. As the aim of the work is to measure the efficiency, inefficiency, and productivity of decision-making units in order to improve them and make them more advantageous by analyzing the sustainable tripod, it is important to choose the most appropriate methodologies for this. Figure 1 shows the sequence of activities carried out in the empirical study process.

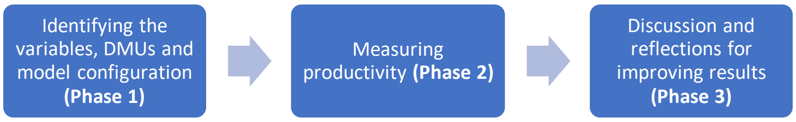

Figure 1 - Stages of the empirical study process

- *First Phase - Identifying variables, DMUs, and model configuration*

As a first step in the study, it was necessary to analyze the choice of variables. We studied the variables that could establish a relationship with the topic of social, operational, and environmental efficiency. By reviewing the literature, using published articles to analyze the output and input data on a case-by-case basis and establish the variables in the empirical study in a real-world company that could return the most favorable results for improving sustainability. In addition, unstructured interviews were conducted with company experts who guided the paths to be taken and provided the important data and variables to be used.

Twelve unstructured interviews were conducted over three months with experts in ESG, Safety and Environment, Maritime Planning, Operations, and Results to collect data for an analysis of ship efficiency. The interviews were essential to define input and output variables and identify DMUs, which in this case were the ships of three companies. In addition to defining variables and DMUs, the interviews also provided specific data on greenhouse gas (GHG) emissions, fuel volume, number of workers, and TEU capacity. This data was collected from various sources, including experts in Safety and Environment and Maritime Planning, as well as Operations and Results managers. Information on TEU-moved cargo and Net Operating Revenue (ROL) was also obtained from interviews with Results specialists.

With the data provided by the company, direct observation of the operation was essential in order to arrive at the models, DMUs, and variables used through an analytical study. DEA with DDF Malmquist was chosen due to its adequacy in treatment for cases where there are undesirable outputs. Through this analytical study, the output orientation was determined, where the values of greenhouse gas emissions are inverted and kept as output, an approach known as Multiplicative Inverse (MLT) [21]. This method was chosen to maximize output and, consequently, minimize greenhouse gases.

- *Second phase - Measuring productivity*

In this phase, the intention is to analyze the evolution or regression over the years of the ships of the empirical study company. To do this, the Malmquist DDF was used to show productivity and observe the reasons for this change [25].

- *Third Phase – Discussion and reflections for improving results*

The last phase is to analyze the results of the previous phases and send them to the company to report on existing inefficiencies. The company's specialists will be able to observe and develop ideas so that the inefficient decision-making units can produce like the efficient ones. This process allows action plans to be developed so that it is possible to improve the productivity and efficiency of ships through the ESG approach. It is important to emphasize that this process is continuous and cyclical because after this study has been carried out, it is necessary to repeat this step-by-step process every year to observe the evolution of the improvements proposed in this third phase.

4 Results and discussion

This section presents the results obtained by calculating efficiency and productivity, as well as a discussion of the results of the literature review and unstructured interviews with experts, pre-data modeling, and post-calculation results.

As a first step in the empirical study, a literature review was carried out to find out the information needed to evaluate the eco-efficiency of maritime transport. In conjunction with this study, unstructured interviews were conducted with two ESG specialists from the company, a specialist from the safety and environment area, a specialist from the maritime planning area, a specialist from the operations area, and a specialist from the results area.

The unstructured interviews with the two ESG specialists were held every two weeks for three months. Firstly, the meetings sought to define the decision-making units and the input and output variables for modeling the approach. The main points highlighted were the importance of using greenhouse gases, as they are the undesired output variable, where we should minimize them, seeking to understand the differences in efficiency in relation to each DMU.

Through these interviews, the DMUs were defined as the ships, and the information related to the inputs and outputs was collected through new interviews. The interview with the operations specialist was important for acquiring input on the number of workers and the Teus capacity of the ship. The fuel volume input was collected after the meeting with the maritime planning specialist. The desired outputs of net operating revenue and cargo handled in TeUs were acquired through the unstructured interview with the results specialist. Finally, the undesirable output was collected after two interviews with the company's safety and environmental specialists.

Table 1 contains the statistical summary of data collected from 2020 to 2022 for the six variables defined for the study. The values in bold and italics represent the values that were estimated using the Excel estimation formula. The estimated values were the six variables for the Self 2 and M2 ships that could not be collected, as well as the values for the volume of fuel used and greenhouse gas emissions from the ships of the M and W companies, which did not provide information for privacy reasons.

Table 1 – statistical summary of selected variables

Ship	Capacity Teus ($x10^3$)			Fuel Volume (kT L)			Workers			Cargo Moved Teus ($x10^3$)			Total GHG Emissions (k T CO_2e)			ROL (R$ MM)		
Year	**2020**	**2021**	**2022**	**2020**	**2021**	**2022**	**2020**	**2021**	**2022**	**2020**	**2021**	**2022**	**2020**	**2021**	**2022**	**2020**	**2021**	**2022**
Min.	0.2	0.2	0.2	4.3	5.0	3.6	24.0	20.0	23.0	0.4	0.6	0.4	13.1	13.9	16.3	1.3	1.2	2.2
1st Q	0.2	0.2	0.2	6.6	6.3	6.5	26.0	23.0	25.0	1.6	1.2	1.8	17.2	15.4	21.5	5.7	2.9	10.4
Median	0.5	0.5	0.5	7.6	7.6	7.8	28.0	25.0	27.0	12.1	11.8	11.7	19.3	16.7	22.4	43.3	28.0	58.9
Mean	0.8	0.8	0.8	7.3	7.5	7.5	28.3	25.5	26.7	19.7	21.3	22.7	20.7	18.7	22.3	39.6	38.3	60.1
3rd Q	1.4	1.4	1.4	8.2	8.9	8.8	31.5	28.0	28.5	25.1	30.0	33.5	23.0	20.0	23.0	63.3	57.2	98.8
Max.	2.0	2.0	2.0	9.4	9.9	9.8	35.0	32.0	31.0	89.1	96.1	133.1	33.2	31.3	32.2	104.0	133.2	175.0

The DDF Malmquist productivity index was used to evaluate the evolution of the efficiency and technology of ships from 2020-2022. The DDF model allows observing the directional vector of the total productivity index by directing the undesirable output towards the desired direction when evaluating production over the years [32].

The DDF results showed substantial efficiency improvements for several ships between 2020-2021, with W3 and M3 having the highest productivity growth due to large catch-up effects. However, M2 had a significant drop in productivity to 0.05, mainly due to reduced efficiency from lower cargo and revenue compared to 2020. Between 2021-2022, 10 ships had productivity growth per the DDF model. M2 rebounded with the highest productivity increase to 27.3, largely due to a major catch-up effect from higher efficiency. Self 1 and M3 had the lowest productivity between these years.

Comparing 2020 to 2022, the DDF model showed only four ships with productivity growth above 1. The frontier shift was below 1 for all ships, indicating technological change over the period did not make the ships more efficient overall. However, M1 had a substantial 42.9 catch-up effect despite the minimal frontier shift, demonstrating a large efficiency increase between 2020 and 2022.

In summary, the DDF Malmquist model provided insight into the directional effects on undesirable output when evaluating efficiency and technology changes over time. The model showed larger impacts on year-over-year efficiency changes compared to multi-year technological progress. The ships with the best overall productivity growth balancing efficiency, emissions reductions, and operational growth based on the DDF model were M1, which had a major catch-up effect, and W3, which showed high productivity across the periods analyzed. Table 2 summarizes the DDF Malmquist Productivity Index results, showing the four higher and lower values ordered by productivity growth in the 2020 – 2022 period.

Table 2 - DDF Malmquist Productivity Indices (2020 - 2022)

Years	***Comparison 2020 - 2021***			***Comparison 2021 - 2022***			***Comparison 2020 - 2022***		
Models	***DDF Malmquist***			***DDF Malmquist***			***DDF Malmquist***		
Indexes	***cu***	***fs***	***mi***	***cu***	***fs***	***mpi***	***cu***	***fs***	***mpi***
M1	0.67	0.38	0.25	1.18	5.35	6.31	42.9	0.11	4.54
Self 4	1	0.53	0.53	3.11	0.74	2.3	3.5	0.65	2.27
Self 5	0.29	1.02	0.29	2.1	0.41	0.85	1.63	0.78	1.28
W1	0.33	1.08	0.36	1	3.8	3.8	4.51	0.23	1.05
…	**…**	**…**	**…**	**…**	**…**	**…**	**…**	**…**	**…**

W2	0.7	0.48	0.34	0.31	5.27	1.65	1	0.34	0.34
W5	3.22	1.86	6.01	0.93	3.04	2.84	0.62	0.5	0.31
W4	1	0.35	0.35	1	1.99	1.99	0.59	0.34	0.2
Self 3	0.19	0.95	0.18	1	0.55	0.55	0.19	0.99	0.19
W6	0.73	0.74	0.54	0.41	3.4	1.4	0.16	0.47	0.08

The DDF Malmquist index showed a limited number of efficient ships over the years, as it was sensitive to changes in undesirable greenhouse gas emissions output. Reducing emissions impacted desirable outputs under the DDF model's directional vector approach. Company ships were more often efficient, likely due to their lower operational control from buying partner ship space.

The DDF Malmquist index showed that partner ships experienced the most technological and efficiency evolution from 2020 to 2021. However, company ships increased substantially in revenues for cargo and lowered emissions from 2020-2022, reflecting their growing sustainability culture. The company's capacity, cargo, revenue and employee growth contributed to productivity gains from 2020-2022 especially.

While the company DDF efficiency and productivity grew for their own ships, opportunities exist to collaborate and buy space on more partner ships to match other shipowners. The company could also serve as a benchmark by increasing operational interaction.

Ongoing annual DDF Malmquist measurement will be key for the company to guide sustainability and efficiency goals, benchmark against other shipowners, and focus on lowering emissions while growing revenue and cargo. The cyclical DDF application can track the impact of emissions as the company's capacity and operations expand.

5 Conclusions

Meeting growing coastal shipping demand in Brazil poses challenges for the company analyzed and other shipowners to expand capacity while reducing environmental impact. The UN SDGs underscore the need to cut maritime emissions by 70% by 2050, making efficient, productive shipping crucial.

This study assessed self and partner ship productivity and efficiency from 2020-2022, emphasizing sustainability. Analyzing this period was key to identifying efficient, productive benchmark ships. The DMUs were vessels transporting the analyzed company's cargo.

The DDF and Malmquist models showed company ships increased efficiency by balancing outputs. Partner ships exhibited lower effectiveness as the company did not operate their transported cargo. Efficient DMUs serve as optimal benchmarks for improvement.

From an academic point of view, the study contributes to the logistics and operations management fields by developing a structured, data-driven approach to incorporate sustainability targets in efficiency measurement. From the practitioner's perspective, the developed approach provides a straightforward way to incorporate sustainable goals when defining benchmarks.

The study is limited to only three companies in a period of three years. Further investigations involving more companies in larger timeframes could improve results and help develop a more generalized approach.

Periodic application of this approach will drive continuous evolution and control for the company, aligning with the step-by-step approach. The study contributes by incorporating the DDF/Malmquist models into sustainable maritime evaluation. Future research could leverage Big Data DEA, nonlinear optimization, and Machine Learning with DEA to predict new DMU efficiency. Overall, various methodologies can provide comprehensive insights into eco-efficient maritime transportation and inform decision-making.

References

1. Akabane, G.K., De Carvalho, D.L.: Análise Exploratória da Sustentabilidade Ambiental do Transporte por Cabotagem: Um Estudo de Caso em uma Empresa Transportadora na Rota Manaus (AM) a Santos (SP). Brazilian Journal of Business. 4, 2469–2494 (2022). https://doi.org/10.34140/bjbv4n4-057
2. O, E.S.G.L.: Relatório de Sustentabilidade Sumário. (2021)
3. Liao, Y.H., Lee, H.S.: Using a Directional Distance Function to Measure the Environmental Efficiency of International Liner Shipping Companies and Assess Regulatory Impact. Sustainability (Switzerland). 15, (2023). https://doi.org/10.3390/su15043821
4. Nunes, A., Teixeira, M., Rocio, A.R., Mendes, L.A.: Navegação De Cabotagem Brasileira. BNDES Setorial. 391–436 (2017)
5. Lin, A.J., Chang, H.-Y., Hung, B.: Identifying Key Financial, Environmental, Social, Governance (ESG), Bond, and COVID-19 Factors Affecting Global Shipping Companies—A Hybrid Multiple-Criteria Decision-Making Method. Sustainability. 14, 5148 (2022). https://doi.org/10.3390/su14095148
6. Oloruntobi, O., Chuah, L.F., Mokhtar, K., Gohari, A., Rady, A., Abo-Eleneen, R.E., Akhtar, M.S., Mubashir, M.: Decarbonising ASEAN coastal shipping: Addressing climate change and coastal ecosystem issues through sustainable carbon neutrality strategies. Environ Res. 240, 117353 (2024). https://doi.org/10.1016/j.envres.2023.117353
7. Pérez, I., González, M.M., Trujillo, L.: Do specialisation and port size affect port efficiency? Evidence from cargo handling service in Spanish ports. Transp Res Part A Policy Pract. 138, 234–249 (2020). https://doi.org/10.1016/j.tra.2020.05.022
8. Agüero-Tobar, M.A., González-Araya, M.C., González-Ramírez, R.G.: Assessment of maritime operations efficiency and its economic impact based on data envelopment analysis: A case study of Chilean ports. Research in Transportation Business and Management. 46, (2023). https://doi.org/10.1016/j.rtbm.2022.100821
9. Kaiser, B.C.S., Santos, R.S., Caiado, R.G.G., Scavarda, L.F., Netto, P.I.: Efficiency Assessment of Public Transport Vehicles Using Machine Learning and Non-parametric Models. In: M, L.S. V, G, M.F.F., C, G. dos R.J., and M, C.M. das D.J. (eds.) Springer Proceedings in Mathematics and Statistics. pp. 207–220. Springer (2022)

10. Caiado, R.G.G., Heymann, M.C., Silveira, C.L.R., Meza, L.A., Quelhas, O.L.G.: Measuring the eco-efficiency of Brazilian energy companies using DEA and directional distance function. IEEE Latin America Transactions. 18, 1844–1852 (2020). https://doi.org/10.1109/TLA.2020.9398625
11. Caiado, R.G.G., de Freitas Dias, R., Mattos, L.V., Quelhas, O.L.G., Leal Filho, W.: Towards sustainable development through the perspective of eco-efficiency - A systematic literature review. J Clean Prod. 165, 890–904 (2017). https://doi.org/10.1016/j.jclepro.2017.07.166
12. Martinez-Moya, J., Mestre-Alcover, A., Sala-Garrido, R.: Connectivity and competitiveness of the major Mediterranean container ports using 'Benefit-of-the-Doubt' and 'Common Sets of Weights' methods in Data Envelopment Analysis. Maritime Economics & Logistics. (2023). https://doi.org/10.1057/s41278-023-00258-w
13. Krmac, E., Mansouri Kaleibar, M.: A comprehensive review of data envelopment analysis (DEA) methodology in port efficiency evaluation. Maritime Economics & Logistics. 25, 817–881 (2023). https://doi.org/10.1057/s41278-022-00239-5
14. Charnes, A., Cooper, W.W., Rhodes, E.: Measuring the efficiency of decision making units. Eur J Oper Res. 2, 429–444 (1978). https://doi.org/10.1016/0377-2217(78)90138-8
15. Torres, Y.L.: Análise da performance dos times do campeonato brasileiro de futebol masculino de 2019 através do Network DEA. Petropolis: UFF. (2021)
16. Lins, M.P.E., Meza, L.A.: Análise envoltória de dados e perspectivas de integração no ambiente de apoio à decisão. Rio de Janeiro: Coppe/UFRJ. (2000)
17. Souza, P.C.T., Wilhelm, V.E.: Uma introdução aos modelos DEA de eficiência técnica. Curitiba. Cienc Cult. 121–139 (2009)
18. Banker, R.D., Charnes, A., Cooper, W.W.: Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis. Manage Sci. 30, 1078–1092 (1984). https://doi.org/10.1287/mnsc.30.9.1078
19. Scheel, H.: Undesirable outputs in efficiency valuations. Eur J Oper Res. 132, 400–410 (2001). https://doi.org/10.1016/S0377-2217(00)00160-0
20. Tschaffon, P.B., Meza, L.A.: Um estudo de outputs indesejáveis em DEA com aplicação no setor de distribuição de energia elétrica. XLVIII SBPO-Simpósio Brasileiro de Pesquisa Operacional. 533–544 (2011)
21. Heymann, M.C., Paschoalino, F.F., Caiado, R.G.G., Lima, G.B.A., Pereira, V.: Evaluating the eco-efficiency of loading transport vehicles: A Brazilian case study. Case Stud Transp Policy. 9, 1688–1695 (2021). https://doi.org/10.1016/j.cstp.2021.06.018
22. Färe, R., Grosskopf, S., Noh, D.W., Weber, W.: Characteristics of a polluting technology: Theory and practice. J Econom. 126, 469–492 (2005). https://doi.org/10.1016/j.jeconom.2004.05.010
23. Luenberger, D.G.: Benefit functions and duality. J Math Econ. 21, 461–481 (1992). https://doi.org/10.1016/0304-4068(92)90035-6
24. Chung, Y.H., Färe, R., Grosskopf, S.: Productivity and undesirable outputs: A directional distance function approach. J Environ Manage. 51, 229–240 (1997). https://doi.org/10.1006/jema.1997.0146
25. Junior, A.M. de M., Wilhelm, V.E.: Índice de malmquist aplicado na avaliação da Produtividade de soja na região de Guarapuava. Revista Capital Científico do Setor de Ciências Sociais Aplicadas. 4, 15 (2006)
26. Färe R., G.S.L.C.A.K.: Production Frontiers. Cambridge, Great Britain: Cambridge University Press. (1994)

27. Zhou, P., Ang, B.W., Han, J.Y.: Total factor carbon emission performance: A Malmquist index analysis. Energy Econ. 32, 194–201 (2010). https://doi.org/10.1016/j.eneco.2009.10.003
28. Yu, M.M., Rakshit, I.: Target setting for airlines incorporating CO2 emissions: The DEA bargaining approach. J Air Transp Manag. 108, 102376 (2023). https://doi.org/10.1016/j.jairtraman.2023.102376
29. Chen, C., Lam, J.S.L.: Sustainability and interactivity between cities and ports: a two-stage data envelopment analysis (DEA) approach. Maritime Policy and Management. 45, 944–961 (2018). https://doi.org/10.1080/03088839.2018.1450528
30. Heymann, M.C., Paschoalino, F.F., Brito, G., Lima, A., Gusmão, R.G., Pereira, V.: Machine Translated by Google Avaliando a ecoeficiência de veículos de transporte de carga : um estudo de caso brasileiro. 9, 1688–1695 (2021)
31. Zamora Torres, A.I., González García, J.: Eficiencia del transporte de carga internacional mexicano: análisis por entidad federativa a través del Índice Malmquist, 2010-2014. Economía Teoría y Práctica. 125–144 (2019). https://doi.org/10.24275/etypuam/ne/502019/zamora
32. Geng, N., Liu, Z., Wang, X., Meng, L., Pan, J.: Measurement of Green Total Factor Productivity and Its Spatial Convergence Test on the Pig-Breeding Industry in China. Sustainability (Switzerland). 14, (2022). https://doi.org/10.3390/su142113902