https://doi.org/10.3311/PPtr.38266

Periodica Polytechnica Transportation Engineering, 53(1), pp. 31–49, 2025

Analysis of Sustainable Efficiency of Freight Transport in Major European Economies: An Integrated Multi-Region Input-Output and DEA Approach

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Received: 06 September 2024, Accepted: 26 October 2024, Published online: 12 November 2024

Abstract

This paper integrates the multi-region input-output model (MRIO) and data envelopment analysis (DEA) methods to analyze the freight transport efficiency in Europe. Social, economic, and environmental influences were combined into a sustainable efficiency rating of the freight transport sector of Germany, France, Italy, Spain, and the Netherlands. First, the freight transport sector's carbon footprint (CFP) was quantified using the MRIO model. The lifecycle-based CFP emissions of freight transport activities were assessed using a dataset from 2000 to 2018. Nineteen stochastic model-based MRIO lifecycle assessments were built for each country. Secondly, sixty instances of DEA models were created using a linear program for each mode in the selected countries. Thirdly, the sustainable efficiency scores were determined for each freight transport mode in each country over four periods: 2000–2004, 2005–2009, 2010–2014, and 2015–2018. The results illustrate that the sustainable efficiency score of inland, water, and air transport modes ranged from 0.38 to 1.

Keywords

input-output model, freight transport sector, data envelopment analysis, sustainability, efficiency score

1 Introduction

Freight transportation entails moving goods from one location to another, facilitating the distribution of goods to various places where production and consumption take place. Transportation is essential for economic development. A freight transport network consists of two main elements: the infrastructure (lines such as highways, railroads and pipelines, and nodes e.g., seaports and airports) and the carriers responsible for product delivery. Shippers utilize various freight carriers, including trains and lorries, airplanes and ships, to transport goods (Abbood and Meszaros, 2023). The transportation industry plays a pivotal role in advancing the global economy (Boldizsár et al., 2022). It is a fundamental driver in enhancing mobility, urban growth, and trade. Moreover, it facilitates the linkage of cities, nations, and distant areas across the globe, fostering connectivity. This sector has generated millions of employment opportunities and boosted the efficiency of various other sectors within the global economy. Over the last 25 years, the European Union (EU) transport sector has witnessed significant growth, with an increase of 36%. In 2020, the transportation industry's total volume of goods reached 3,326,345 million tonne-kilometers (as shown in Fig. 1). 52% of all transportation activities in the EU are attributed to road transport, 28% to maritime transport, and 11.5% to rail transport. The remaining transportation modes are considerably less significant (Eurostat, 2023).

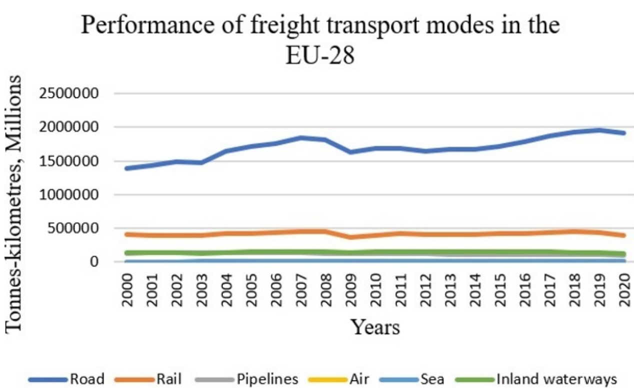

Fig. 1 Performance of freight transport modes in the European Union-28 from 2000 to 2020, measured in millions of tonne-kilometers (Source: own editing based on Eurostat database (Eurostat, 2023))

Cite this article as: Abbood, K., Mészáros, F., Alatawneh, A. (2025) "Analysis of Sustainable Efficiency of Freight Transport in Major European Economies: An Integrated Multi-Region Input-Output and DEA Approach", Periodica Polytechnica Transportation Engineering, 53(1), pp. 31–49. https://doi.org/10.3311/PPtr.38266

On the other hand, emissions from the freight transportation sector constitute a substantial portion of the worldwide and local burden of greenhouse gases (GHGs) and significant air pollutants (David, 2024). Nowadays, transportation via rail or road, air or water, primarily relies on fossil fuels and is a substantial source of GHGs, specifically carbon dioxide (CO_2) and air pollution. This has a direct impact on the health of thousands of individuals, particularly in urban centers and metropolitan regions (Matthias et al., 2020). The ecological sustainability of the freight transport sector is commonly assessed based on the reduction of CFP emissions it achieves. Unsurprisingly, life cycle assessment (LCA) is the most frequently utilized methodology applied for quantifying CFP emissions. This is due to its holistic approach, which enables the assessment of a broader spectrum of environmental impacts. Nonetheless, even though lifecycle (LC) based methods are extensively employed to identify the significant sources of environmental effects within the life cycle of the evaluated system, they have limitations when it comes to serving as standalone approaches for verifying eco-efficiency and minimizing environmental impacts within intricate sectoral systems. To this end, data envelopment analysis (DEA) emerges as a linear optimization method utilized to assess the relative effectiveness of multiple similar entities when the production process involves various inputs and outputs. DEA also enables the calculation of attainable target operating conditions that can transform inefficient entities into relatively efficient ones, making it a valuable tool for benchmarking objectives. DEA is now more frequently integrated with LC methods to establish LC-based benchmarks. These combined methodologies are broadly applicable and primarily depend on the accessibility of the input and the output data for a group of similar entities known as decision-making units (DMUs). In this context, the LCA + DEA approach was officially introduced in 2010 as a fusion of LCA and DEA for assessing the operational and ecological efficiency of comparable entities (Vázquez-Rowe and Iribarren, 2015).

This research aims to assess the efficiency of the freight transport sector of the top five industrial nations in Europe from a sustainability point of view. Therefore, a multi-region input-output (MRIO)-LCA approach and the DEA were integrated to scrutinize this sector in the selected countries. This integration offers a thorough comprehension of the total CFP emissions generated by the three freight transport modes: inland/surface transportation, air transportation, and waterborne transportation. The MRIO model was utilized to measure the carbon emissions produced by the freight transport industry. The paper assesses the environmental effect of freight transport activities in the chosen nations over nineteen years (2000–2018), taking into consideration their international trade connections with the global economy. Furthermore, the integration determines the economic, environmental, and social efficiency of the three modes for each country by using the CFP emissions values and other variables, including the number of employees in each mode (EMPE), total hours worked by employees (H-EMPE), nominal capital stock (K), freight carried by each mode, and the total economic output (TEO) of each mode. Data were sourced from the World Input-Output Database (WIOD), the Eurostat database (Eurostat, 2023), and the Organization for Economic Cooperation and Development (OECD) database. The novelty of the current study is that it evaluated the three dimensions of sustainability in the freight transport industry in the selected countries. In the literature, most research focused on one or two dimensions, especially economics. Furthermore, the freight transport industry is rarely studied separately since all studies generally analyze the transportation sector. Moreover, studies analyze one or two countries regarding the transportation sector, contrasting with the current study, which assessed five industrial countries in Europe.

The structure of the paper is as follows: Section 2 shows a review of relevant work within the scientific literature, Section 3 addresses the structure of the proposed approach, Section 4 shows the outcomes and discussions, and Section 5 summarizes the findings of this paper and outlines potential avenues for future studies.

2 Literature review

The current work proposes an integration of MRIO analysis and sustainable efficiency methods. As a result, the pertinent literature is scrutinized in two sections, aligning with these methods. The concluding section of the review addresses the research deficit and delineates the current study's contributions.

2.1 Utilizing MRIO analysis for evaluating the CFP emissions

Among the techniques employed in performing LCA, the input-output analysis (IOA) is a well-known and robust method. This is due to its effectiveness in assessing sustainability impacts across entire industries without requiring extensive and exhaustive data collection (Suh et al., 2006).

Generally, it allows for broader system boundaries, such as incorporating supply chains at regional, national, or international levels. It offers a sturdy framework for examining any process or item, where the relating production processes or service activities can be quantified in monetary term values that serve as input into an input-output (IO)-LCA model (Miller and Blair, 2009). While IO-LCA was initially seen as an environmentally expanded version of IOA, it is currently employed for evaluating the social, economic, environmental, and ecological components of sustainable development (Ezici et al., 2020). Although IO-LCA methods provide valuable benefits for tracking direct and indirect (supply chain) effects at regional or national economic scales, past research has predominantly relied on a single-region IO-LCA approach with a domestic technology assumption. This leads to significant constraints in assessing sustainability impacts on a worldwide economic scale (Park et al., 2016). As a result, the MRIO approach is increasingly used to address the constraints of single-region IO-LCA methods (Ezici et al., 2020).

Wiedmann et al. (2011) highlighted the reasons behind the current prevalence of MRIO analysis as the primary approach in IOA, including a discussion of its benefits and proposed directions for future research on the model. Here are a few of the identified benefits of MRIO: it supports tracking the effects associated with various activities within supply chains at local, national, and global levels, which often span across multiple industries or even countries; it can be expanded for use in proceeding forecasts and predictions; it serves as a solid foundation for in-depth examination of the intricate effects of products and processes on global supply chains. In their research, Zhang et al. (2015) analyzed energy usage by evaluating the realized energy consumption to illustrate how energy moves through the seven regions of China. Using monetary MRIO data and energy statistics from the years 2002 and 2007 for Chinese provinces, they considered both the direct and indirect energy consumption, as well as the overall input and output of energy within the examined regions. In a previous study, Abbood and Meszaros (2023) assessed the CFP emissions of the freight transportation industry in seven industry based countries during a fifteen-year period, considering the global trade connections with other regions worldwide. The study explored the correlation between the global CFP, the gross domestic product (GDP), the size of population, the urbanization level, and the size of country. Fifteen stochastic model-based (SMB) MRIO-LCA were constructed across 35 pivotal industries for each country. Statistical modeling techniques were applied to evaluate the carbon emissions. Furthermore, Abbood and Mészáros (2023) conducted another analysis to evaluate the environmental footprint associated with transportation practices in Hungary in terms of carbon emissions and energy usage. This analysis considered Hungary's international trade connections with other countries. The Hungarian economy has been integrated into a MRIO-LCA framework, comprising forty key economies, such as Hungary, the United States, Russia, China and other countries, as well as the rest of the world countries.

2.2 The evaluation of sustainability efficiency using DEA

Manufacturing sectors utilize finite and sustainable energy sources to conduct their processes and manufacture goods for various industries and consumers. Sustainable efficiency has been commonly employed to evaluate how particular industries, products, or services contribute economically and socially in relation to their environmental effects. Sustainable efficiency is determined by comparing the economic advantages of a DMU's action against the environmental consequences of that task (Egilmez et al., 2013). DEA is a commonly employed quantitative method for conducting sustainable efficiency assessments. DEA is commonly applied to evaluate and compare the performance of DMUs as it is a robust benchmarking technique rooted in linear programming (Sembill et al., 2009). DEA has been employed in assessing various entities' performance, such as banks, healthcare facilities, publicly traded companies, educational institutions, and more. DMUs can represent various entities, including countries, industries, universities, and others, with the goal of benchmarking a specific DMU against the others in the studied set. The DEA trials provide an efficiency score for each DMU, which typically ranges from 0 to 1, indicating their relative performance based on the ratio of production (output) to utilization (input) in a certain manufacturing process (Ezici et al., 2020). For instance, a MRIO model was integrated with DEA to investigate the building sector's energy efficiency in China on a provincial scale (Wen et al., 2020).

Wang et al. (2022) introduced a novel approach to evaluate the ecological sustainability of supply chains. This method combines an MRIO model with DEA. By integrating economic and environmental considerations within supply chains, the approach generates a green-degree indicator while considering the limitations related to energy consumption structure. This technique allows for the assessment of the renewable and the non-renewable energy consumption incorporated in global supply chains, ultimately quantifying the environmental sustainability of these supply chains. In another research while exploring the potential impact of protectionist policies on the environment in developing nations, Wang et al. (2022) employed a comprehensive assessment model that combines MRIO, DEA, and scenario analysis.

Egilmez et al. (2016) developed a hybrid method for evaluating the sustainability performance of thirty-three food production businesses in the United States of America by integrating fuzzy DEA with an IO-based LC evaluation. First, the impacts of energy, forestland footprint, fishery footprint, the total released carbon dioxide, and total quantity of water consumed were assessed using the economic input-output (EIO)-LCA. Then, the outcomes of the EIO-LCA model were employed as inputs of the DEA method with the output (total economic output) to assess the eco-efficiency. Moreover, they also established a hierarchical methodology consisting of two phases to evaluate the environmental effects of a country's food manufacturing industries. First, the EIO-LCA model was used to identify the effects of land footprint, water extraction, energy usage, and CFP. Later, the EIO-LCA model outcomes were utilized as inputs for the DEA, with the quantity of food products generated by each food industry representing the output (Egilmez et al., 2014).

Based on the literature review of integrating MRIO and DEA, as indicated in Table 1, no research has been conducted to assess the efficiency of the European freight transport industry from a sustainability viewpoint. Thus, this current work evaluates the efficiency of the three pillars (environment, society, and economics) of sustainability in the freight transport industry in Europe during a nineteen-year study period. The scope of sustainability aspects involved the CFP emissions, number of employees in each mode, price levels of intermediate input, compensation of employees, freight carried by each mode, and the total economic output of each mode.

3 Methodology

Section 3 addresses the integrated method of MRIO and DEA in detail. In addition, the process of collecting and preparing data is described. Fig. 2 illustrates the three theoretical phases involved in the suggested method. The MRIO outputs were used as inputs in the DEA phase.

3.1 Collection of data

The data utilized in this study were gathered from diverse official sources like the World Input-Output Database (WIOD), the Eurostat database (Eurostat, 2023), and the

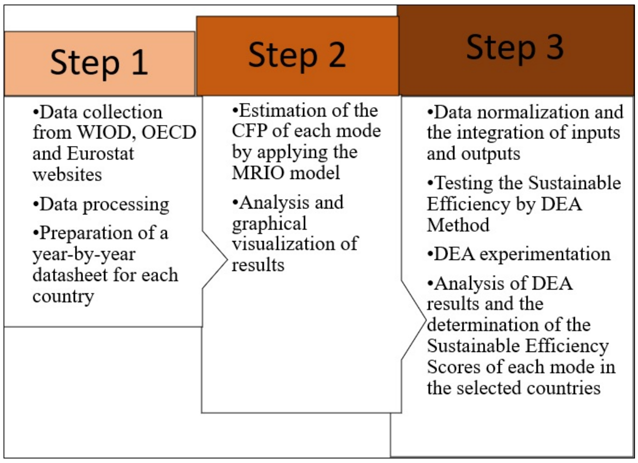

Fig. 2 The theoretical approach of the suggested method

Table 1 Studies that used the output of MRIO and EIO as inputs of the DEA tool

	Study	Methodology	Scope	Input	Output
1	Ezici et al. (2020)	MRIO and DEA	"US manufacturing industries"	"Renewable and non-renewable energy consumption"	"Overall economic production"
2	Egilmez et al. (2013)	EIO-LCA and DEA	"The 53 major U.S. manufacturing sectors"	"Environmental impacts include greenhouse gas emissions, energy consumption, water withdrawals, hazardous waste, and toxic discharges"	"Overall economic production"
3	Egilmez et al. (2016)	EIO-LCA and DEA	"The 33 sectors of food production in the United States"	"Energy, forestland, and fishery footprint, the total emitted carbon dioxide, and the total amount of water used"	"Total economic output"
4	Egilmez et al. (2014)	EIO-LCA and DEA	"The 33 US food manufacturing sectors"	"Land footprint, water withdrawal, energy consumption, and carbon footprint"	"The quantity of food items generated by each food industry"
5	Wen et al. (2020)	MRIO and DEA	"China's construction sector"	"Amount of total embodied energy used"	"The gross product of the provincial construction sector"
6	Wang, et al. (2022)	MRIO and DEA	"Global supply chain"	"Energy consumption"	"The economic output"

Organization for Economic Cooperation and Development (OECD). The WIOD and OECD are current and extensive MRIO databases that comprise a time series of symmetrical IO tables spanning from 2000 to 2014 and 2000 to 2018, respectively (Abbood et al., 2023). These tables encompass the global economy, including forty major nations (based on their gross domestic product) and the rest of the world. Within each country's economy, there are thirty-five industries, with sixteen falling under the manufacturing category (Ezici et al., 2020). The analysis assumes a fixed product sales structure, meaning every industry has its own sales structure accounting for the output of products sold to intermediate and final users (Abbood et al., 2023). The Eurostat database (Eurostat, 2023) contains huge statistical information about all sectors of all European countries. The authors collected the other variables, such as the number of employees in each mode, total hours worked by employees, freight carried by each mode, and nominal capital stock, which were involved in the integrated method of this study from the Eurostat database website (Eurostat, 2023).

3.2 The MRIO model framework

The MRIO model was used to measure the effects of the freight transport industry of the selected nations at different levels, including those related to production, domestic, and international supply chain impacts. The economies of the selected countries were integrated into a multi-region input-output (MRIO) life cycle assessment framework in which 40 major economies, including the US, China, Russia, and others, as well as the rest of the world (ROW), were modeled to analyze global carbon footprint implications. The WIOD and OECD database classification assumes that each country's economy comprises 35 vital industries. A total of 1,435 (41 × 35 = 1,435) industries make up the worldwide structure of the international economy of each country that was studied in this research. The technique is innovative in that the MRIO model was constructed in a stochastic manner, taking into account global trade-related risks. The top carbon generated by industries and nations was examined using data analytics and statistical modeling techniques. The three steps of developing the MRIO model are further explained.

3.2.1 Mathematical background of deterministic MRIO

In the deterministic MRIO framework, the matrix $\left(\boldsymbol{A}_{ij}^{rs}\right)_t$ serves as the main requirement matrix. Each row of this matrix $\left(\boldsymbol{A}_{ij}^{rs}\right)_t$ depicts the inputs required from various local and international industries during producing one output unit. In the applied MRIO model, i represents the input from nation r to industry j in country s. Remark: both i and j are identical, with each being thirty-five and representing the entire number of industries inside a given country. The model also includes forty-one nations, and the rest of the globe, designated by r and s, with uniform values. Based on the core premise of linearity for the MRIO framework, the total output vector for a certain economic output can be computed.

$$\boldsymbol{x}_t^r = \left(I - \left(\boldsymbol{A}_{ij}^{rs}\right)_t\right)^{-1}\left(\boldsymbol{f}_i^t\right)_t \tag{1}$$

The variable $\left(\boldsymbol{f}_i^t\right)_t$ is a vector containing just production in monetary terms from manufacturing sector i in region r, with all other components set to 0. Furthermore, I represents the identity matrix, where all elements are zeros except for the diagonal entries, that are one. The vector $\boldsymbol{x}_t^r$ shows the total output caused by changes in the final production within nation r. This concept, $\left(I - \left(\boldsymbol{A}_{ij}^{rs}\right)_t\right)^{-1}$, is also known as Leontief's inverse. After determining the overall output vector, carbon emissions may be calculated by multiplying each sector's production by the corresponding carbon emissions per output in monetary terms ($\boldsymbol{B}_t$).

$$\boldsymbol{C}_t = \boldsymbol{B}_t\left(I - \left(\boldsymbol{A}_{ij}^{rs}\right)_t\right)^{-1}\left(\boldsymbol{f}_i^t\right)_t \tag{2}$$

In this scenario, $\boldsymbol{C}_t$ represents the vector encompassing the comprehensive environmental consequences, such as GHG emissions. The multiplier for environmental impact is denoted as B, which constitutes a matrix having diagonal components that represent measures such as the global warming potential (GWP) per economic production in monetary terms. The GWP is computed by aggregating the total GHG emissions from individual sectors and subsequently applying conversion coefficients acquired from the US Environmental Protection Agency (EPA).

3.2.2 Mathematical background of stochastic MRIO

In the stochastic MRIO framework, both the total requirement matrix $\left(\left(\left(\boldsymbol{A}_{ij}^{rs}\right)_t\right)^{-1}\right)'$ and the final demand variable $\left(\boldsymbol{f}_i^r\right)_t'$ are regarded as random variables characterized by defined mean and standard deviation values. The mean values are adjusted to correspond with the data points acquired from the WIOD and OECD datasets. Furthermore, the standard deviation values are generated from the means by scaling them with a factor known as k, which is initially set to 10%. This first assumption assumes a 10% fluctuation. Given the total requirement matrix $\left(\boldsymbol{I} - \left(\left(\boldsymbol{A}_{ij}^{rs}\right)_t\right)^{-1}\right)'$

and the final demand (in this study, represented by the economic production of each manufacturing industry), denoted as $\left(f_i^r\right)_t'$ below, where $x_t^{r\prime}$ denotes the stochastic total economic output, which includes both direct and global supply chain contributions, see Eq. (3).

$$x_t^{r\prime} = \left(\left(I - \left(A_{ij}^{rs}\right)_t\right)^{-1}\right)' \left(f_i^r\right)_t' \quad (3)$$

Once the stochastic total economic output, denoted as $x_t^{r\prime}$, is calculated, it becomes straightforward to determine the collective CFP of all sectors across the 41 countries, as shown in Eq. (4). In the deterministic MRIO model, these totals were determined by multiplying the total economic production with a matrix B_t (diagonal entries reflecting the GWP per million dollars of economic activity). In the stochastic scenario, where both factors are subject to uncertainty, Monte Carlo simulation is utilized to determine the mean and the standard deviation values for the resultant total impacts on GWP.

$$C_t' = B_t \left(\left(I - \left(A_{ij}^{rs}\right)_t\right)^{-1}\right)' \left(f_i^r\right)_t' \quad (4)$$

3.2.3 Monte Carlo simulation

The Monte Carlo simulation is a strategy for forecasting outcomes that combines repetitive random sampling with statistical analysis. It is associated with simulating random experiments for specific scenarios where the exact outcomes are unknown (Raychaudhuri, 2008). In this study, Monte Carlo experiments were conducted to estimate confidence intervals for the total CFP of the European freight transport industry. To achieve this, we used the Monte Carlo Simulation Method to construct thirty replications of the stochastic MRIO model for CFP for each year between 2000 and 2018. In total, we conducted 570 experiments by simulating for all nineteen years, repeating the process thirty times (Abbood et al., 2023). Subsequently, we estimated the average and standard deviation of the thirty samples for each year of the CFP. The stages involved in the Monte Carlo simulation are as follows:

1. Compute the overall CFP impact for every year from 2000 to 2018.
2. Generate thirty separate replications for each year.
3. Conduct thirty replications for each analyzed year, covering the period from 2000 to 2018, with a CFP focus.
4. Determine the mean and standard deviation by analyzing data from the thirty samples.

3.3 Normalizing data and the proposed DEA method

3.3.1 Data normalization

After running the MRIO and calculating the CFP emissions values for each freight transport mode in each country, the values of the CFP as well as the values of other variables, including the number of employees in each mode, total hours worked by employees, nominal capital stock, freight carried by each mode, and the total economic output of each mode, were normalized, because there is a disparity in the data's scale resulting from various units. For example, the CFP emissions are measured in million tons, while the number of employees is measured in numbers. Thus, the dataset generated by the MRIO model and other collected variables were normalized using the mean normalization approach. Table 2 displays normalized statistics for each nation's three types of freight transport during the first period (2000–2004). This normalization procedure has been utilized extensively in prior DEA investigations (Raychaudhuri, 2008). Mean normalization was accomplished by computing each input's and output's mean and dividing each input or output by its average (Egilmez et al., 2013). For instance, the freight carried by the three modes, inland transport, water transport, and air transport, of the German freight transport sector in the 2000–2004 period is 2,240,634, 1262, and 36,711 (thousands of tons), respectively, and the average is 759,536. Thus, the normalized number of these values is calculated by dividing each value on the average, and the results are 2.95, 0.0017, and 0.0483, respectively.

3.3.2 The developed DEA method

DEA is a mathematical method introduced by Charnes et al. (1978) that blends linear programming and production theory. DEA's purpose is to evaluate comparable parts using specified inputs and outputs. Charnes et al. (1978) observed that this assessment should prioritize "decision-making efficiency". As a result, the object evaluated in this comparison is a DMU. DMUs might take the form of schools, manufacturing units, nations, hospitals, or states. The objective of DEA is to evaluate the efficiency with which chosen DMUs produce specified outputs using chosen inputs as the basis for comparison (Egilmez and McAvoy, 2013). Drawing inspiration from the productivity equation, Ramanathan defined the effectiveness or proficiency of a DMU as the quotient of overall outputs divided by overall inputs (Ramanathan, 2003). DEA aims to evaluate efficiency by either maximizing

Table 2 The normalized CFP and other variables of the freight transport sectors in each country between 2000 and 2004

Country	DMU's name	CFP	EMPE	H-EMPE	K	Freight carried	TEO
	Inland transport mode	2.763	2.659	2.659	2.596	2.939	2.456
France	Water transport mode	0.075	0.045	0.044	0.078	0.004	0.221
	Air transport mode	0.162	0.297	0.296	0.325	0.057	0.323
	Inland transport mode	2.772	2.714	2.713	2.119	2.950	1.949
Germany	Water transport mode	0.124	0.083	0.082	0.597	0.002	0.412
	Air transport mode	0.104	0.204	0.203	0.284	0.048	0.639
	Inland transport mode	2.460	2.682	2.690	2.522	2.982	2.349
Spain	Water transport mode	0.115	0.075	0.074	0.109	0.005	0.168
	Air transport mode	0.424	0.241	0.235	0.369	0.013	0.482
	Inland transport mode	2.833	2.632	2.632	2.552	2.973	2.499
Italy	Water transport mode	0.077	0.193	0.193	0.225	0.006	0.216
	Air transport mode	0.090	0.175	0.174	0.222	0.020	0.285
	Inland transport mode	1.829	2.433	2.486	2.042	2.858	1.985
Netherlands	Water transport mode	1.008	0.193	0.180	0.399	0.012	0.552
	Air transport mode	0.162	0.373	0.332	0.559	0.129	0.462

CFP = Total carbon footprint, EMPE = employees in each mode, H-EMPE = Total hours spent by workers, K = Nominal capital stock, TEO = Total economic output.

outputs or minimizing inputs using linear programming optimization. Its key advantage lies in avoiding subjective weighting when benchmarking similar units. It calculates an overall performance score termed "efficiency", indicating how effectively inputs are used to generate predefined outputs (Hermans et al., 2008).

In the current research, an input-oriented DEA model utilizes the findings from MRIO analysis to pinpoint the sustainable efficiency of the European freight transport sector. Many researchers have employed combinations of EIO-LCA, MRIO, and DEA to address diverse ecological and ecological sustainability issues. This combined approach arises from the necessity of establishing sustainability standards while conducting life cycle impact assessments. For instance, Ezici et al. (2020) used a cradle-to-gate MRIO and DEA technique to investigate the US manufacturing industries' global dependency on renewable and non-renewable energy from 1995 to 2014. The MRIO models were developed to assess the impacts of worldwide energy consumption and economic output on manufacturing industries. The energy-related consequences were then combined into aggregate totals for the renewable and the non-renewable energy use. The MRIO data used as inputs in the second phase (DEA) were compared to output (total economic output) to assess the US companies' environmental efficiency.

Moreover, the EIO-LCA and DEA models were combined to evaluate the environmental efficiency of the industrial sectors in the US. First, the EIO-LCA assessed the consequences of GHG emissions, energy consumption, water extraction, hazardous waste creation, and toxic chemical discharge using each sector's total economic output. The EIO-LCA results were then employed as inputs in the DEA model together with the overall economic production, which served as the DEA's output (Egilmez et al., 2013). In addition, Egilmez et al. (2016) utilized the output of the EIO-LCA, which are the impacts of energy, forestland, and Fishery footprint, the total emitted carbon dioxide, and the total amount of water, as inputs of the DEA to evaluate the sustainability performance of thirty-three food manufacturing industries in the US.

The current study utilized the MRIO to calculate the CFP emissions of the three modes in the selected countries. This MRIO model is different since it employs a stochastic method while factoring in uncertainties associated with global trade connections. After calculating these CFP values, they were used as inputs for the second phase of the method, which calculates sustainable efficiency by applying the DEA tool. The proposed method in this study is unique since:

1. it uses a deterministic and stochastic MRIO model to identify the CFP emissions, and the Monte Carlo experiments were also conducted to estimate confidence intervals for the overall CFP;
2. the study focuses on analyzing the freight transport industry solely in the biggest industrial European countries;
3. it combines the CFP with other economic and social variables to have a comprehensive understanding of the sustainability performance in this sector;

4. the method uses the latest input-output tables from 2000 to 2018 that were provided in both WIOD and OECD.

In this context, since the input (total CFP, number of employees in each mode, total hours worked by employees, nominal capital stock, and freight carried by each mode) categories represent environmental, economic, and social effects and the output (total economic output) is the economic value added, the term used to describe production efficiency is known as the "sustainable efficiency" score. Therefore, this research incorporates DEA as a benchmarking approach, consolidating freight transport sectors' environmental, social, and economic impacts into a unified sustainability performance score. In this context, the existing literature contains numerous similar techniques that have employed DEA models for measuring sustainability performance, such as (Egilmez and McAvoy, 2013; Ezici et al., 2020; Korhonen and Luptacik, 2004; Kuosmanen and Kortelainen, 2005). The representation for the general input-oriented DEA multiplier model, as suggested by (Egilmez et al., 2014), is presented in Eq. (5).

Objective function:

$$\max_q = \sum_{r=1}^{k} \mu_r y_{ro}. \tag{5}$$

Subject to:

$$\sum_{i=1}^{m} v_i x_{io} = 1, \tag{6}$$

$$\sum_{r=1}^{k} \mu_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0 \quad j = 1, \ldots, n,$$

$$\mu_r, v_i \geq 0. \tag{7}$$

In this model, μ_r stands for the output multiplier, v_i is the input multiplier, o represents the specific DMU in focus, k signifies the count of outputs, m denotes the number of inputs, j is the total number of DMUs, y_{rj} corresponds to the quantity of output r generated by DMU j, and x_{ij} represents the amount of input i utilized by DMU j. The weighted outputs for the DMU under evaluation are summed by the objective function.

The DEA combines several inputs and outputs with the goal of reducing inputs while achieving a given outcome. When the combined input from the other DMUs fails to produce the intended output, the DMU under evaluation is regarded as being on the efficient frontier. When inputs from other DMUs can create the output of the DMU under assessment, the DMU is considered inefficient because the inputs from other DMUs were able to generate greater output for the DMU in issue.

This research uses an input-oriented DEA multiplier model, as the major objective is to decrease negative economic, environmental, and social consequences while maintaining an equal level of overall economic production. The developed DEA model is described as follows.

Objective function:

$$\max z = \varepsilon_j{}' \sum_{i=1}^{m} v_i \times x_{ij'} \text{ for } j' = 1 \ldots M. \tag{8}$$

Subject to:

$$\varepsilon_J \Big/ \sum_{i=1}^{m} v_i \times x_{ij} \text{ for } j = 1 \ldots M, \tag{9}$$

$$v_i \geq 0, \tag{10}$$

where j indicates the overall economic output of the DMUs (freight transportation modes) under consideration. This mathematical approach is computed using linear optimization techniques, and the sustainable efficiency ratio is calculated by determining the inverse of the variable z. The linearized model ran three times (number of modes) in each period for each nation to determine the most beneficial long-term efficiency values across all modes of freight transport.

4 Results and discussion

The current study is unique because it focuses on investigating the efficiency of the three modes of the freight transport sector (inland transport, water transport, and air transportation) in the top five European industrial nations: France, Germany, Spain, Italy, and the Netherlands. The DEA method and MRIO model are integrated to draw a clear understanding of how sustainable these three modes are in the selected countries. The MRIO model is utilized to estimate the CFP emissions caused by these modes in the mentioned countries. This approach examined the LC-based CFP emissions associated with freight transport activities within the selected countries from 2000 to 2018, considering their international trade connections worldwide. Specifically, nineteen stochastic model-based MRIO assessments were constructed for each examined country, encompassing thirty-five major industries. Statistical modeling tools were utilized to evaluate and quantify the CFP emissions. The outcomes of the MRIO were applied as inputs for the DEA model, as well as the number of employees in each mode, total hours worked by employees, and nominal capital stock of each mode of the freight transport industry of these five nations. The DEA method analyzes the ratio of the outputs to inputs to examine the efficiency. Therefore, the economic output of each mode was considered outputs of the DEA. In this regard, the scope of the study is divided into four phases, which are 2000–2004, 2005–2009, 2010–2014, and 2015–2018. The DEA model ran three times (for each mode) in each period for each country to examine the efficiency of the selected modes.

In the reviewed literature, many studies used the output of the MRIO model as inputs of the DEA, such as Egilmez et al. (2013), who identified the eco-efficiency score of US manufacturing by:

1. calculating the GHG emissions, energy use, water withdrawals, hazardous waste generation, and toxic releases of each sector;
2. evaluating the eco-efficiency of these sectors by comparing the inputs to the economic output, which was considered the output of the DEA model, of US manufacturing sectors.

The findings are explained in two phases. The first round shows the outcomes of the MRIO model, and the second phase addresses the sustainable efficiency of each country’s freight transport industry.

4.1 MRIO results

In Section 4.1, the outcomes of each mode of the freight transport industry for the selected nations are presented. The total impacts of CFP on inland, water, and air transport are shown in Figs. 3 to 5, respectively. The expression "total impacts" pertains to the combined effects of on-site and supply-related impacts in each country.

4.1.1 Inland transport mode

Italy is identified as having the most significant share of CFP emissions in the inland sectors, accounting for a substantial 46.17% of the total emissions among the countries

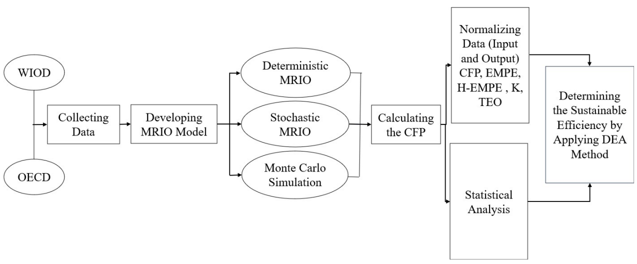

Fig. 3 The realization of the integrated method

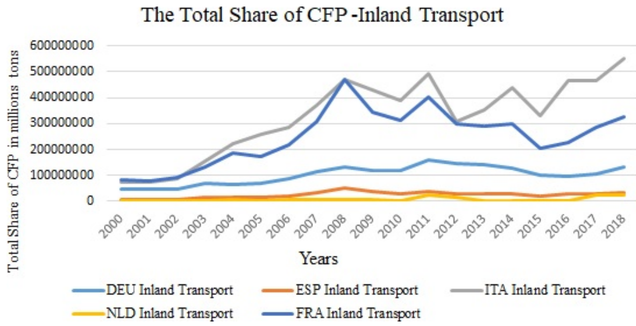

Fig. 4 The entire share of CFP by the inland transportation mode

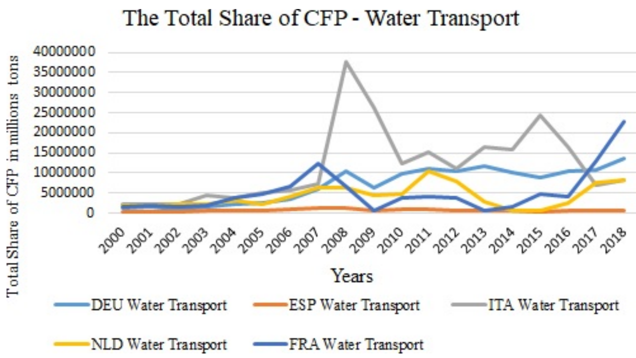

Fig. 5 The entire share of CFP by the water transportation mode

studied during the research period. This significant share suggests that Italy's inland sectors, such as transportation, manufacturing, and other industrial activities, are major contributors to carbon emissions in Europe. In addition, France is the second most significant contributor to CFP in the inland sectors, with 35.09% of the total share. Although lower than Italy's contribution, France's share is still considerable, highlighting its impact on inland sector emissions. The remaining countries have much smaller shares of CFP emissions, ranging from 1.05% to 14.23%. This indicates a wide disparity in the carbon footprint among the studied nations, with Italy and France dominating the emissions in inland sectors while other countries contribute less significantly.

Fig. 4 shows that the CFP emissions from Italy and France were inconsistent throughout the study period. Instead, these emissions fluctuated, showing periods of increase and decrease. Italy and France experienced a rise in CFP emissions from 2000 to 2008. This upward trend suggests that inland sector activities, possibly driven by economic growth or increased industrial activities, contributed increasingly to carbon emissions during this period. Also, there was a decrease in CFP emissions in both countries in 2009 and 2010. This decline could be attributed to several factors, such as the global financial crisis of 2008 and 2009, which reduced industrial activity and, consequently, lowered emissions. It might also reflect the implementation of more stringent environmental policies or advancements in energy efficiency within these sectors. Moreover, in 2011, Italy and France saw an increase in CFP emissions, potentially indicating a recovery in economic activity and a corresponding rise in industrial output. However, this increase was followed by a decrease in 2012, suggesting a possible reintroduction of emission control measures or fluctuations in industrial activity. The CFP emissions in these two countries rose again in 2014, followed by a decrease in 2015. This pattern of alternating increases and decreases highlights the volatility and sensitivity of inland sector emissions to various factors, such as economic conditions, regulatory changes, or technological advancements. From 2015 to 2018, the total share of CFP emissions from Italy and France increased steadily, reaching the highest levels in Italy by the end of the study period. This steady rise could be due to sustained economic recovery, increased industrial activity, or perhaps a slower adoption of green technologies during these years. Fig. 4 explains that, in contrast to the fluctuations seen in Italy and France, the other countries studied had relatively stable contributions to CFP emissions throughout the research period. This stability suggests that these countries had more consistent industrial activity, possibly due to better-managed energy efficiency or smaller overall industrial bases compared to Italy and France.

As Table 3 shows, the correlation analysis for the inland transportation mode reveals that the CFP is positively correlated with TEO (r = 0.274, p < 0.01) and H-EMPE (r = 0.234, p < 0.05), indicating that as economic output and labor intensity increase, so do carbon emissions. The EMPE is strongly correlated with both H-EMPE (r = 0.741, p < 0.01) and K (r = 0.750, p < 0.01), highlighting the interconnectedness of labor and capital in driving operational capacity. Freight carried is highly correlated with EMPE (r = 0.707, p < 0.01), H-EMPE (r = 0.980, p < 0.01), and TEO (r = 0.714, p < 0.01), underscoring the critical role of labor in freight operations and its significant contribution to economic output. However, the lack of correlation between CFP and K suggests that capital investments do not directly impact carbon emissions, potentially due to efficiencies in technology or operations.

4.1.2 Water transport mode

Fig. 5 demonstrates that Italy has the highest share of CFP emissions in the water transport sector, accounting for 40.72% of the total emissions among the studied countries. Italy's CFP peaked in 2008, decreased in 2010, rose again in 2015, experienced a sharp drop in 2017, and then saw a slight increase towards the end of the study period. In addition, Germany is the next largest contributor, with 24.23% of the total CFP in water transport. Germany's CFP steadily increased throughout the period from 2000 to 2018, reaching its peak at the end of the study period in 2018. Moreover, France contributes 18.15% of the total CFP in water transport. France's CFP emissions rose from 2000 to 2007, dipped in 2009 to their lowest point, slightly increased between 2010 and 2012, decreased again in 2013, and then rapidly increased to reach their highest level in 2018. Also, the Netherlands accounts for 14.59% of the total CFP in water transport. The Netherlands saw an increase in CFP from 2000 to 2011, followed by a significant drop to the lowest levels in 2014 and 2015. The CFP share then rose again from 2016 to 2018. Spain has the lowest share of CFP emissions in the water transport sector, contributing just 2.29% of the total. Spain's CFP emissions are characterized by minimal variation and consistently low levels throughout the study period.

The CFP emissions in Italy's water transport sector show significant variability over the years, with notable peaks and troughs. The peak in 2008 suggests a possible period of increased water transport activity or less efficient practices, followed by a dip that might indicate economic or policy changes. The fluctuations highlight the instability in Italy's contribution to CFP in this sector. In contrast

Table 3 Correlation matrix in the inland transportation mode

	CFP	EMPE	H-EMPE	K	Freight carried	TEO
CFP	1.000	0.077	0.234*	−0.152	0.143	0.274**
EMPE	0.077	1.000	0.741**	0.750**	0.707**	0.486**
H-EMPE	0.234*	0.741**	1.000	0.346**	0.980**	0.730**
K	−0.152	0.750**	0.346**	1.000	0.299**	0.307**
Freight Carried	0.143	0.707**	0.980**	0.299**	1.000	0.714**
TEO	0.274**	0.486**	0.730**	0.307**	0.714**	1.000

* Correlation is significant at the 0.05 level (2-tailed).
** Correlation is significant at the 0.01 level (2-tailed).

to Italy, Germany's CFP emissions show a steady upward trend, indicating a consistent increase in water transport activity or possibly higher emissions from this sector. The peak in 2018 suggests that Germany's water transport sector had its most significant environmental impact at the end of the study period. France's trend reveals periods of both growth and decline in CFP emissions. The initial rise followed by a significant dip in 2009 might reflect economic downturns, shifts in transport policies, or changes in energy efficiency. The rapid increase towards 2018 indicates a resurgence in water transport activity or decreased emission control effectiveness. The Netherlands experienced a steady rise in CFP until 2011, after which there was a sharp decrease, particularly in 2014 and 2015. This drop could be due to technological improvements, a reduction in water transport activity, or effective environmental policies. The subsequent rise in CFP suggests a recovery or increased activity in the sector. Spain's water transport sector shows the least variation and the lowest CFP emissions, indicating stable, low-impact operations in this sector across the study period.

Table 4. shows that in the water transportation mode, CFP is strongly correlated with EMPE ($r = 0.805$, $p < 0.01$), H-EMPE ($r = 0.662$, $p < 0.01$), K ($r = 0.765$, $p < 0.01$), and Freight Carried ($r = 0.573$, $p < 0.01$), indicating that higher labor and capital inputs lead to increased carbon emissions. EMPE shows significant correlations with H-EMPE ($r = 0.601$, $p < 0.01$) and K ($r = 0.607$, $p < 0.01$), suggesting a strong link between labor, capital, and operational efficiency. Freight carried is highly correlated with H-EMPE ($r = 0.955$, $p < 0.01$) and K ($r = 0.861$, $p < 0.01$), reflecting the labor and capital intensity required to maximize freight capacity. However, the weaker correlation between CFP and TEO ($r = 0.397$, $p < 0.01$) suggests that while economic output influences emissions, its impact is less pronounced compared to labor and capital factors.

4.1.3 Air transport mode

Fig. 6 shows that Italy has the largest share of CFP emissions in the air transport sector, accounting for 61.88% of the total emissions among the studied European industrial countries. This overwhelming share indicates that Italy's air transport sector is a substantial contributor to the overall carbon footprint in Europe. Italy's CFP emissions in the air transport sector increased steadily, indicating growing air transport activity or possibly less efficient practices from 2000 to 2008. There was a rapid decrease in CFP emissions in 2009, possibly due to economic downturns (e.g., the global financial crisis) or improvements in air transport efficiency. The CFP emissions increased again, reaching high levels in 2011, suggesting a recovery in air transport activity. After a decrease in 2012, emissions peaked in 2014, likely driven by increased air traffic or less stringent emissions controls. There was a rapid decline in emissions in 2015 and 2016, possibly due to policy interventions or advancements in technology. A slight increase towards the end of the study period suggests a minor resurgence in CFP contributions from Italy's air transport sector in 2017 and 2018. In addition, France is the second major contributor to CFP emissions in the air transport sector, accounting for 18.75% of the total emissions. Although significantly lower than Italy, France's

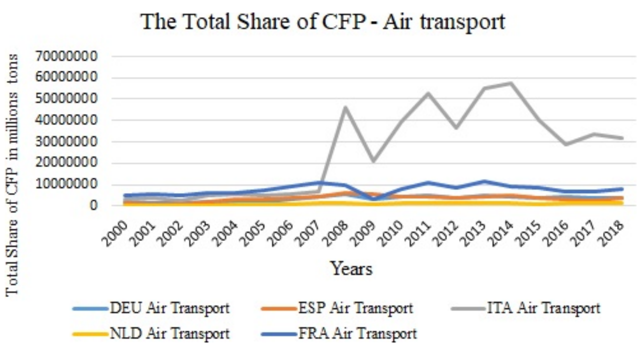

Fig. 6 The entire share of CFP by the air transportation mode

Table 4 Correlation matrix in the water transportation mode

	CFP	EMPE	H-EMPE	K	Freight carried	TEO
CFP	1.000	0.805**	0.662**	0.765**	0.573**	0.397**
EMPE	0.805**	1.000	0.601**	0.607**	0.437**	0.099
H-EMPE	0.662**	0.601**	1.000	0.840**	0.955**	0.190
K	0.765**	0.607**	0.840**	1.000	0.861**	0.506**
Freight carried	0.573**	0.437**	0.955**	0.861**	1.000	0.360**
TEO	0.397**	0.099	0.190	0.506**	0.360**	1.000

* Correlation is significant at the 0.05 level (2-tailed).
** Correlation is significant at the 0.01 level (2-tailed).

contribution is still notable. France's CFP emissions rose steadily from 2000 to 2007, indicating increased air transport activity or emissions during these years. Like Italy, France experienced a decrease in emissions, with the lowest point in 2009, possibly due to economic factors or increased efficiency in air transport. Emissions increased again, peaking in 2013, suggesting a period of high air transport activity or reduced efficiency. A slight decline occurred, indicating stabilization or a modest reduction in emissions from 2014 to 2016. A slight increase in 2018 points to a small rise in air transport activity or emissions. The remaining countries (likely Germany, Spain, and the Netherlands) had much smaller shares of CFP emissions in the air transport sector, with contributions ranging from 2.41% to 8.42%. Their contributions were described as minimal and stable throughout the study period. Germany and Spain contributed almost identical CFP emissions in the air transport sector, suggesting similar levels of air transport activity or comparable emissions control measures. The Netherlands is noted as the lowest contributor among the studied countries, indicating that its air transport sector had the smallest impact on CFP emissions.

The trend in Italy's air transport CFP emissions shows significant fluctuations over time, reflecting periods of growth, decline, and recovery in air transport activity. The sharp rise in emissions until 2008 could be linked to increased air traffic, economic growth, or less efficient aircraft technologies. The rapid decline in 2009 likely reflects the impact of the global financial crisis, leading to reduced air travel and, consequently, lower emissions. The subsequent peaks and declines suggest a cyclical pattern influenced by economic factors, policy changes, and possibly technological improvements in the sector. In addition, France's CFP trends also show periods of increase and decrease, with similar dynamics to Italy's but on a smaller scale. The increase until 2007 reflects growing air traffic, while the dip in 2009 mirrors the economic downturn and its effects on air travel. The peak in 2013 indicates a resurgence in air transport activity, followed by a period of stabilization. However, the other countries' stable and minimal contributions suggest that their air transport sectors were either less active or more efficient in managing CFP emissions compared to Italy and France. The similar contributions of Spain and Germany imply that these countries had comparable levels of air traffic or emissions control measures in place. The Netherlands, being the lowest contributor, likely had a smaller air transport sector or more effective emissions management.

Table 5 depicts that for the air transportation mode, CFP is highly correlated with EMPE ($r = 0.905$, $p < 0.01$), suggesting that labor is a major driver of carbon emissions. CFP also shows moderate correlations with K ($r = 0.479$, $p < 0.01$) and Freight carried ($r = 0.284$, $p < 0.01$), indicating that both capital investments and freight operations contribute to emissions, though to a lesser extent than labor. EMPE is strongly correlated with K ($r = 0.531$, $p < 0.01$) and Freight Carried ($r = 0.421$, $p < 0.01$), emphasizing the role of labor in operational efficiency. The moderate correlation between CFP and TEO ($r = 0.567$, $p < 0.01$) suggests that while economic output impacts emissions, labor remains the most significant factor in driving carbon footprint in air transport.

4.2 The DEA results

The study aims to assess the efficiency of different modes of freight transport in various countries. Efficiency, in this context, is defined not just by economic performance but also by environmental and social considerations, making the assessment more holistic and aligned with the principles of sustainability. The study uses six variables to evaluate efficiency, which are grouped into three categories:

1. Environmental Impact: This includes variables like the CFP emissions. The focus here is on how much pollution or environmental harm each mode of freight transport causes. Lower CFP emissions generally indicate a more environmentally efficient mode of transport.

Table 5 Correlation matrix in the air transportation mode

	CFP	EMPE	H-EMPE	K	Freight carried	TEO
CFP	1.000	0.905**	0.214*	0.479**	0.284**	0.567**
EMPE	0.905**	1.000	0.330**	0.531**	0.421**	0.539**
H-EMPE	0.214*	0.330**	1.000	0.504**	0.956**	0.471**
K	0.479**	0.531**	0.504**	1.000	0.504**	0.395**
Freight carried	0.284**	0.421**	0.956**	0.504**	1.000	0.352**
TEO	0.567**	0.539**	0.471**	0.395**	0.352**	1.000

* Correlation is significant at the 0.05 level (2-tailed).

** Correlation is significant at the 0.01 level (2-tailed).

2. Social Impact: This category includes the number of employees involved in each mode of transport and the total hours worked. These variables reflect the human element of the transport industry, highlighting how many jobs are supported by each mode and the amount of labor required. This could indicate the social sustainability of the mode, where higher employment might be seen as beneficial, but extremely high labor hours could suggest inefficiency or labor exploitation.
3. Economic Impact: The study considers economic outputs such as the nominal capital stock and the amount of freight carried by each mode. Nominal capital stock represents the investment in physical assets (e.g., vehicles, infrastructure), while the freight carried reflects the economic value generated by the transport mode. These indicators help in understanding the economic sustainability and productivity of each transport mode.

First, inland, water, and air transport modes are evaluated and ranked according to their sustainable efficiency. As shown in Table 6, the sustainable efficiency scores for these three types of freight transport vary from 0.38 to 1. Within the freight transport sector, the study identified certain modes in specific countries as fully efficient. Specifically, France's water transport, Germany's air and water transport, Italy's water transport, and both water and air transport in the Netherlands achieved a 100% efficiency rating when compared to other transport modes across the selected countries.

In contrast, the efficiency of air transport in France, Spain, and Italy showed significant fluctuations. The findings indicate that France's air transport sector was particularly inefficient during the 2005–2009 and 2010–2014 periods, with sustainable efficiency scores of 0.76 and 0.55, respectively. Additionally, Spain's air transport sector recorded the lowest sustainable efficiency score of 0.38 during the 2005–2009 period. Italy's air transport also struggled, posting its lowest score of 0.47 between 2015 and 2018. The primary cause of these low sustainable efficiency scores is linked to a decline in the economic output of the air transport industry in these countries over the analyzed periods. Meanwhile, the carbon footprint (CFP) contribution from this sector remained relatively unchanged from previous years, and other influencing factors maintained their impact. Given that sustainable efficiency scores are determined by the ratio of outputs to inputs, the decreased economic output relative to the constant inputs resulted in lower efficiency scores during these periods.

Moreover, for the remaining periods, all other transport modes in these countries were found to have efficiency scores ranging from 0.99 to 1. The authors suggest that, except for the Netherlands, the studied countries' air transport sectors lack efficiency and require improvements, particularly in reducing their CFP. On the other hand, water transport emerged as the most efficient mode, characterized by low CFP emissions and minimal capital costs.

Table 6 The sustainable efficiency of the three modes in the selected countries

Country	DMU's name	The sustainable efficiency score								
		2000–2004	2005–2009	2010–2014	2015–2018	Mean	Min.	Max.	ST. Dev.	Median
France	Inland	1	1	0.99	0.99	0.995	0.99	1	0.005	0.995
	Water	1	1	1	1	1	1	1	0	1
	Air	1	0.76	0.55	1	0.8275	0.55	1	0.1878	0.88
Germany	Inland	0.99	1	1	1	0.9975	0.99	1	0.0043	1
	Water	1	1	1	1	1	1	1	0	1
	Air	1	1	1	1	1	1	1	0	1
Spain	Inland	0.99	0.99	1	1	0.995	0.99	1	0.005	0.995
	Water	0.99	1	1	1	0.9975	0.99	1	0.0043	1
	Air	0.99	0.38	1	0.99	0.84	0.38	1	0.2656	0.99
Italy	Inland	0.99	1	1	0.99	0.995	0.99	1	0.005	0.995
	Water	1	1	1	1	1	1	1	0	1
	Air	1	1	1	0.47	0.8675	0.47	1	0.2295	1
Netherlands	Inland	1	1	0.99	1	0.9975	0.99	1	0.0043	1
	Water	1	1	1	1	1	1	1	0	1
	Air	1	1	1	1	1	1	1	0	1

Although inland transport generates a substantial amount of CFP and demands significant capital investment, it is still considered sustainable across all countries. This is because inland transport positively contributes to the economic output of these countries, balancing its environmental and financial impacts with its economic benefits.

It is crucial to note that most freight transport modes analyzed in the selected countries achieved efficiency scores of 99% or 100%, according to the DEA. Although these modes are associated with significant adverse impacts, such as CFP emissions, they are still regarded as highly efficient. This is mainly because they contribute substantially to the economic output of the countries involved, despite their notable environmental and social effects. DEA evaluates these modes by integrating their environmental and social impacts with the economic value they generate. As a result, while the freight transport modes substantially affect social, economic, and environmental aspects, they can still achieve high sustainable efficiency scores. When considering their combined economic, social, and environmental performance, these modes may even achieve 100% sustainable efficiency. Figs. 7 to 9 show the variety of the efficient scores between the modes of the studied countries.

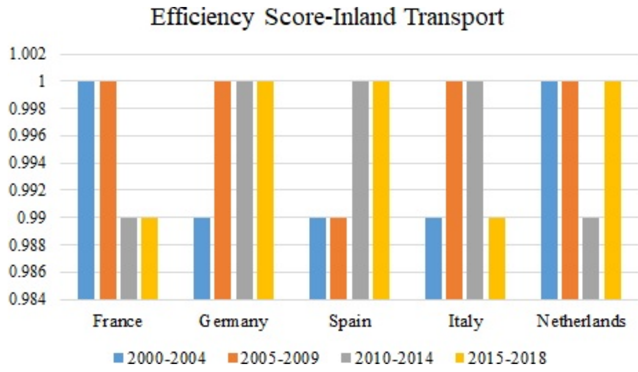

Fig. 7 The sustainable efficiency score of inland transport mode

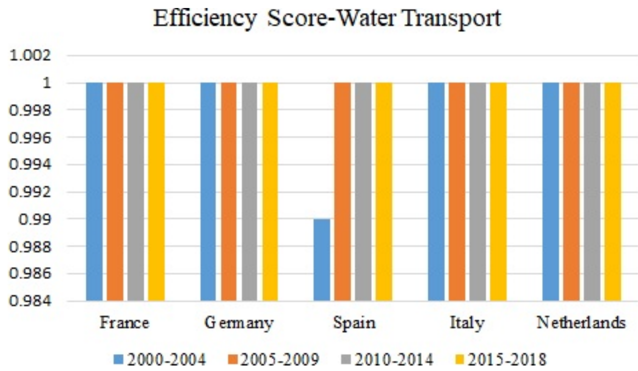

Fig. 8 The sustainable efficiency score of the water transport mode

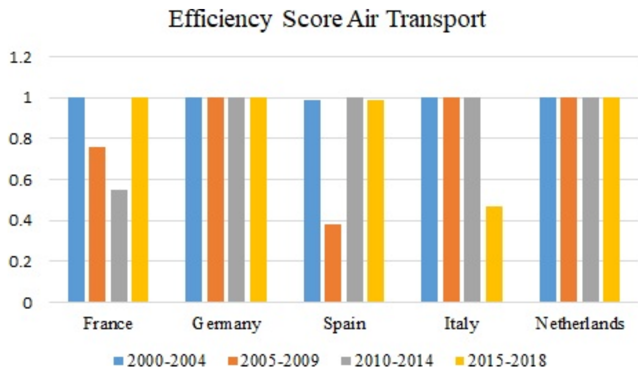

Fig. 9 The sustainable efficiency score of the air transport mode

4.3 Comparison of transportation modes across countries

Section 4.3 presents the results of non-parametric statistical tests used. The Kruskal-Wallis test was conducted to determine if there are statistically significant differences among the three transportation modes across all six variables in the five countries. As shown in Table 7, the results indicate that substantial differences exist for all variables across the three modes ($p < 0.01$). This suggests that the characteristics of each transportation mode vary substantially in terms of their carbon footprint, labor, capital investment, freight capacity, and economic output. These differences highlight the distinct operational and environmental profiles of inland, water, and air transport, which are critical for developing targeted policies to improve sustainability in the freight transport sector.

Following the Kruskal-Wallis test, the Mann-Whitney U test was employed to perform pairwise comparisons between the countries for each transportation mode. Table 8 provides the results of these comparisons, which reveal several significant differences in the variables across the country pairs. For the inland transport mode, significant differences were found in all variables between Germany and Spain, with the exception of Nominal Capital Stock (p=0.42), and between Germany and France, with notable differences in EMPE (p = 0.02) and TEO (p = 0.01). Additionally, Spain and France showed no significant differences in CFP (p = 0.49), while Spain and Italy, as well as Germany and Italy, showed significant differences across all variables.

In the water transport mode, significant differences were observed between Germany and the Netherlands for freight carried (p = 0.01), while Italy and the Netherlands differed significantly in CFP (p = 0.01) and freight carried

Table 7 Kruskal-Wallis test results for transportation modes across the six countries

DMU's name	CFP	EMPE	H-EMPE	*K*	Freight carried	TEO
Inland transport mode	0.00	0.00	0.00	0.00	0.00	0.00
Water transport mode	0.00	0.00	0.00	0.00	0.00	0.00
Air transport mode	0.00	0.00	0.00	0.00	0.00	0.00

Table 8 Mann-Whitney U test results for country pair comparisons across transportation modes

Country	DMU	CFP	EMPE	H-EMPE	K	Freight carried	TEO
	Inland	0.00	0.00	0.00	0.42	0.00	0.00
Germany-Spain	Water	0.00	0.00	0.00	0.00	0.27	0.00
	Air	0.00	0.00	0.00	0.00	0.00	0.00
	Inland	0.00	0.02	0.71	0.00	0.00	0.01
Germany-France	Water	0.00	0.00	0.00	0.00	0.00	0.00
	Air	0.00	0.00	0.00	0.00	0.00	0.00
	Inland	0.00	0.00	0.00	0.00	0.00	0.30
Germany-Italy	Water	0.00	0.00	0.00	0.00	0.00	0.00
	Air	0.00	0.00	0.00	0.00	0.00	0.00
	Inland	0.00	0.00	0.00	0.00	0.00	0.00
Germany-Netherlands	Water	0.00	0.00	0.00	0.00	0.01	0.00
	Air	0.00	0.00	0.00	0.00	0.00	0.00
	Inland	0.49	0.00	0.00	0.00	0.22	0.00
Spain-France	Water	0.00	0.00	0.02	0.04	0.00	0.00
	Air	0.00	0.00	0.00	0.39	0.00	0.00
	Inland	0.00	0.00	0.00	0.00	0.00	0.00
Spain-Italy	Water	0.00	0.00	0.00	0.00	0.00	0.00
	Air	0.00	0.00	0.00	0.15	0.13	0.00
	Inland	0.00	0.00	0.00	0.00	0.00	0.00
Spain-Netherlands	Water	0.00	0.00	0.00	0.00	0.06	0.00
	Air	0.00	0.00	0.00	0.00	0.00	0.05
	Inland	0.51	0.00	0.00	0.00	0.00	0.00
France-Italy	Water	0.03	0.00	0.00	0.00	0.00	0.21
	Air	0.62	0.00	0.00	0.03	0.00	0.35
	Inland	0.00	0.00	0.00	0.00	0.00	0.00
France-Netherlands	Water	0.00	0.00	0.00	0.00	0.00	0.02
	Air	0.00	0.00	0.00	0.03	0.86	0.00
	Inland	0.00	0.00	0.00	0.00	0.00	0.00
Italy-Netherlands	Water	0.01	0.00	0.00	0.00	0.03	0.03
	Air	0.00	0.01	0.00	0.62	0.00	0.00

($p = 0.03$). These results indicate variability in the environmental and operational efficiency of water transport between these countries.

For the air transport mode, nearly all country pairs showed significant differences across the variables, particularly in labor-related metrics (EMPE and H-EMPE) and Nominal Capital Stock, underscoring the distinct operational characteristics of air transport across Europe. These findings emphasize the need for tailored strategies in each country to enhance the sustainability of freight transportation.

4.4 Comparison across countries for transportation modes

Section 4.4 examines the differences across France, Germany, Spain, Italy, and the Netherlands in terms of six specified variables for the three transportation modes. The analysis also employs the Kruskal-Wallis test to identify significant differences across countries, followed by the Mann-Whitney U test to compare the transportation modes within each country. The Kruskal-Wallis test results, presented in Table 9, indicate significant

Table 9 Kruskal-Wallis test results for countries based on the transport modes

Country	CFP	EMPE	H-EMPE	*K*	Freight carried	TEO
France	0.000	0.000	0.000	0.000	0.000	0.000
Germany	0.000	0.000	0.000	0.000	0.000	0.000
Spain	0.000	0.000	0.000	0.000	0.000	0.000
Italy	0.027	0.000	0.000	0.000	0.000	0.000
Netherlands	0.000	0.000	0.000	0.000	0.000	0.000

differences among the five countries across all variables for the inland, water, and air transport modes ($p < 0.05$). Notably, Italy shows a marginally higher p-value for CFP ($p = 0.027$), suggesting that its carbon footprint differs slightly less from the other countries compared to the other variables, which uniformly present significant differences ($p = 0.000$). These results highlight the varying operational and environmental characteristics of the transportation modes across the countries, underscoring the need for country-specific policies to address the unique challenges and opportunities in each region's freight transport sector.

The Mann-Whitney U test results provide a more granular view of the differences between transportation modes within each country, as shown in Table 10. In France, significant differences were observed between inland and water transport modes for CFP ($p = 0.030$) and between water and air transport modes for CFP ($p = 0.000$), indicating that the environmental impact of different transport modes varies significantly. However, the comparison between inland and air transport modes did not yield significant differences in CFP ($p = 0.470$), suggesting that these modes have similar carbon footprints.

Germany exhibited significant differences across all comparisons for CFP, with the most notable difference between inland and water transport ($p = 0.000$). This indicates substantial variability in carbon emissions between these modes. The significant differences in TEO between water and air transport ($p = 0.015$) suggest that these modes also differ in their economic contributions.

In Spain, the results were consistent across all transportation mode comparisons, with significant differences for all variables ($p = 0.000$). This suggests a clear distinction between the environmental and economic impacts of each transport mode in Spain. Italy's results, on the other hand, show some variations; significant differences were observed between inland and water transport for CFP ($p = 0.020$) and between water and air transport for both CFP ($p = 0.020$) and TEO ($p = 0.708$). The high p-value for the TEO comparison between water and air transport suggests that, while there is a significant difference in CFP, the economic output of these modes is more similar.

In the Netherlands, the Mann-Whitney U test revealed significant differences in CFP across all transportation modes, particularly between water and air transport

Table 10 Mann-Whitney U test results for transportation mode comparisons within countries

Country	DMUs name	CFP	EMPE	H-EMPE	*K*	Freight carried	TEO
	Inland - Water	0.030	0	0	0	0	0
France	Inalnd - Air	0.470	0	0	0	0	0
	Water - Air	0	0	0	0	0	0.212
	Inland - Water	0	0	0	0	0	0
Germany	Inalnd - Air	0	0	0	0	0	0
	Water - Air	0.053	0	0	0	0	0.015
	Inland - Water	0	0	0	0	0	0
Spain	Inalnd - Air	0	0	0	0	0	0
	Water - Air	0	0	0	0	0	0
	Inland - Water	0.020	0	0	0	0	0
Italy	Inalnd - Air	0.580	0	0	0	0	0
	Water - Air	0.020	0	0	0	0	0.708
	Inland - Water	0	0	0	0	0	0
Netherlands	Inalnd - Air	0	0	0	0	0	0
	Water - Air	0.012	0	0	0	0	0.012

(p = 0.012), indicating diverse environmental impacts. However, the similarity in other variables suggests that while CFP differs, operational aspects such as labor and capital investment are consistent across modes.

5 Conclusion and future work

The social, environmental, and economic efficiency of the freight transport sector's modes (inland, water, and air) of the top five European industrial countries were evaluated by integrating the MRIO and the DEA models.

The first phase of the evaluation method was to estimate the CFP emissions of the freight transport modes of the selected nations over nineteen years from 2000 to 2018. The findings of the inland transportation mode show that Italy has the greatest percentage of CFP, accounting for 46.17% of the total share of the analyzed nations for the study period. Furthermore, France is regarded as the second greatest contributor to CFP's overall share, accounting for 35.09%. The remaining countries' carbon footprints varied from 1.05% to 14.23%. Regarding the total CFP share by the water transport mode, the results show that Italy is the dominant country, with 40.72 % of the total share. Germany is the second highest contributor, accounting for 24.23% of the total effect. France and the Netherlands were responsible for 18.15% and 14.59% of the CFP in the water transport sector, respectively. Finally, the results of the air transport mode show that Italy is the main contributor, accounting for 61.88% of total CFP emissions. France is the second greatest contributor to CFP emissions, accounting for 18.75% of the total effect. The CFP in the remaining nations ranges from 2.41% to 8.42%.

The second phase of the evaluation process was to analyze the sustainable efficiency of these three modes of the freight transport industry in the selected nations. To accomplish this goal, five inputs, the CFP emissions that were calculated in the first phase of each mode, the number of employees in each mode, total hours worked by employees, nominal capital stock, and freight carried by each mode, and one output, which is the total economic output produced by these three modes in each country, were utilized to run the DEA model. The outcomes demonstrated that the sustainable efficiency score of the three modes of the freight transport sector ranged from 0.38 to 1. Among the freight transport sector modes, France's water transport, Germany's air and water transport, Italy's water transport, and the Netherlands' water and air transport were found to be 100% efficient in the study with respect to other modes in the selected countries. On the contrary, the efficiency of the air transport mode of France, Spain, and Italy was unsteady. The results reveal that France's air transport was inefficient during 2005–2009 and 2010–2014, with sustainable efficiency scores of 0.76 and 0.55, respectively. In addition, Spain's air transport recorded a low sustainable efficiency score of 0.38 in the 2005–2009 period, while Italy's air transport reported a low sustainable efficiency score of 0.47 in the 2015–2018 period.

The statistical analyses further elucidated the differences across countries and transportation modes. The Kruskal-Wallis and Mann-Whitney U tests revealed significant variations in carbon footprint, labor inputs, capital stock, and economic outputs across the five countries and between the three transportation modes. These findings highlighted the unique environmental and economic profiles of each country's transportation sector, emphasizing the need for country-specific strategies to enhance efficiency and reduce carbon emissions.

The authors believe that the current study provides an extensive understanding of the sustainable efficiency of the three modes of the freight transport industry in the selected nations. This efficiency evaluation can offer essential guidance for decision-makers to improve this sector. Sustainable efficiency explains that even though some transport modes have social and environmental impacts, they positively contribute to the economy and can be efficient. In contrast, others can be less efficient because they significantly impact these countries' environment and economies despite enhancing the total economic output.

One of the study's drawbacks is a lack of data identifying additional social and economic variables that may be included in the current investigation. Also, no recent data can be used in the MRIO and DEA models to understand the behavior of this sector efficiently to date. To analyze this sector more precisely, the authors plan to expand the study by considering more variables such as taxes, accidents caused by each mode, income, and others. Also, this integration of the MRIO and DEA models can be applied to assess any industry. Finally, a comprehensive study can be done by investigating the efficiency of the freight transport sector globally and extending the period.

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