sustainability

MDPI

Article

Green Transportation and Logistics Performance: An Improved Composite Index

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Abstract: This article constructs an environmental logistics performance index (ELPI) for assessing the overall performance in green transportation and logistics practices of 112 countries. The index is measured by logistics performance index (LPI), CO_2 emissions and oil consumption from the transport sector, using a range-adjusted measure (RAM) of the data envelopment analysis (DEA). ELPI effectively reflects the tradeoff between logistics efficiency and environmental protection in transportation. This article analyzes the impact of income and region on ELPI scores and discusses those countries' reduction potential in oil consumption intensity and carbon intensity. The main finding of the research work is that ELPI is strongly correlated with LPI, and countries with high performance in LPI generally perform well in ELPI. Similar to the characteristics of LPI, ELPI is also closely related to income and region. During our study period, high income countries performed best, while Sub-Saharan Africa countries performed worst. However, some exceptions such as Venezuela, RB and Benin, indicate that the level of development of logistics performance and green transportation can outperform or lag behind their income or region group peers.

Keywords: transportation; logistics performance index; CO_2 emissions; oil consumption; data envelopment analysis

1. Introduction

Negative externalities of transportation have long been recognized. Trade globalization has continuously increased the demand for international freight transportation, which has promoted the development of international logistics. Meanwhile, logistics systems are under increasing pressure due to the impact of the natural environment. Globally, transportation accounted for one-fourth of total emissions in 2016, around 8 Gt CO_2, 71% larger than in 1990 [1]. Among them, CO_2 emissions from freight transportation accounted for 42% of total transport-related CO_2 emissions [2,3], and it is expected to increase to 60% by 2050 [4]. The global sustainable development of transportation and logistics systems have been put on the agenda. However, countries have different environmental efficiencies in transportation. Consequently, it is necessary to consider the sustainability factor when comparing the differences in logistics performance among countries, that is, green transportation.

To measure the logistics performance of countries, the World Bank and the Turku Institute of Economics in Finland proposed the national logistics performance index (LPI) in 2007, which became the first comprehensive evaluation index for the development level of logistics performance in various countries. The LPI is derived from a standardized questionnaire taking the survey online and uses principal component analysis to composite the data into a single index. LPI values range from 1 to 5, with 1 indicating lower logistics performance and 5 indicating higher logistics performance. New versions were released in 2010, 2012, 2014, 2016, and 2018. Six components of LPI with the explanations below [5]:

1. Customs (*Cust*): The efficiency of customs and border management clearance.
2. Infrastructure *(Infra)*: The quality of trade and transportation infrastructure.
3. Services *(Serv)*: The competence and quality of logistics services.
4. Timeliness *(Time)*: The frequency with which shipments reach consignees within scheduled or expected delivery times,
5. Tracking and tracing *(Track)*: The ability to track and trace consignments.
6. International shipments *(Ship)*: The ease of arranging competitively-priced shipments.

The LPI is an interactive benchmarking tool to identify possible challenges and opportunities in relation to the performance of trade logistics. Arvis [5] compared the logistics performance differences among different countries, regions and income groups, and discussed different strategies to improve the logistics performance of different groups in the world. It is mentioned that low-income countries mainly focus on logistics infrastructure and transport facilitation, while middle-income countries intend to improve logistics skills and services as well as trade regulations. High-income countries, on the other hand, put more emphasis on green logistics and information systems. This means that richer regions have greater opportunities to promote sustainable development.

Green logistics is an environmentally friendly logistics system which includes greening of various processes in logistics, such as transportation, warehousing and distribution, and green recycling of reverse logistics such as waste recycling and disposal [6]. Many empirical researches have been conducted on green logistics to explore several aspects of green logistics initiatives in specific countries or regions in the past decade [7,8]. On the premise of the sustainable development agenda, Q. and C. [9] found that green logistics is a key and ideal policy choice for promoting global sustainable development by assessing the environmental impact of logistics. Centobelli et al. [10] developed the WH2 framework to determine the classification of green aims, green practices and technological tools through a diffusion investigation of logistics service providers (LSPs). The fossil fuel consumption of transportation is the main source of environmental pollution caused by logistics activities. Therefore, some literature discusses the development of green logistics from the perspective of green transportation [4,11].

Although the previous literature discussed the key factors of green logistics implementation and practical recommendations, there was little concern about the comparison of effects of logistics or transportation on the environment between countries around the world. According to the literature research, the general way to evaluate the green efficiency of logistics or transportation was to build a DEA model with capital, labor and energy as input indicators, and sectoral GDP as expected output indicators with carbon emissions as non-expected output indicators. The problem would be solved if statistics on these indicators were available from the World Bank or other authorities for most countries. Unfortunately, only statistics on energy consumption and carbon emissions in the transport sector are available. This is the main cause of the limited related research.

In the absence of data, scholars have tried to use LPI and environmental factors to describe the status of green logistics development in various countries. Kim and Min [12], with the green logistics performance index (GLPI) by the ratio of LPI score to environmental performance index (EPI) composite score, presented a completely different ranking to either the EPI or the LPI. It should be noticed that using a ratio cannot systematically reflect the efficiency of inputs and outputs. Martí et al. [13] applied the data envelopment analysis (DEA) method to synthesize an overall LPI index and conducted a rank sum test on the logistics performance scores of various income and region groups. They tried three cases of using six components as input–output variables, which was an attempt of DEA in LPI reassessment. However, their work did not consider environmental issues. The research of Mariano [14] is closest to that goal. They evaluated the efficiency in the relationship between logistics performance and CO_2 emissions of the transport sector. They used DEA's slacks-based measure (SBM) method to combine CO_2 emissions of the transport sector with LPI and constructed a low carbon logistics performance index (LCLPI). They ranked 104 countries by their LCLPI scores to determine which countries performed best in low carbon logistics. However, their ranking result cannot explain that some low-income countries with low LPI scores, such as Togo, are efficient in LCLPI. This article argues that these countries exhibit environmental friendliness mostly because of their underdeveloped traffic and the low total CO_2 emissions of transportation, which makes them appear to be efficient. Therefore, the heterogeneity of countries should be taken into account in the efficiency evaluation. The purpose of this article is to discuss whether countries with higher logistics performance index (LPI) scores have better performance in green transportation. To answer this question, we proposed an environmental logistics performance index (ELPI) to provide a comprehensive measure of the logistics performance of selected countries and the environmental efficiency of their transport sector. ELPI is constructed using the dataset of the international logistics performance index (LPI) and the transport sector's CO_2 emissions intensity and oil consumption intensity for quantitative analysis. The dataset is analyzed by an environmental range-adjusted measure (RAM) model of the data envelopment analysis (DEA) proposed by Sueyoshi and Goto [15]. This article evaluates ELPI of different countries in different periods and discusses the ranking differences with LPI. One-way analysis and a kruskal-wallis test are respectively used to examine the differences of income and region groups, and further analyzes the variation trend of the mean of each group.

It is worth emphasizing that ELPI is a better auxiliary index of LPI than previous indices because of several advantages: Firstly, this index systematically considers the impact of energy consumption and CO_2 emissions, which is more comprehensive than considering only CO_2 emissions. Then, using the RAM model, we can assess the comprehensive performance from the perspective of natural emission reduction, which is more conducive to helping countries find their inefficiencies in green transportation. In addition, the impact of the heterogeneity of the national economy has been considered, which makes ranking results more reasonable.

To sum up, this index makes up for the deficiency of LPI in environmental assessment. It helps to conduct a comprehensive evaluation of the logistics performance, energy consumption and CO_2 emissions of transport in various countries. In the absence of monitoring data on green logistics practices, this index can be used as a possible scheme to evaluate the green logistics performance in various countries. Furthermore, best practices based on the ELPI score can provide guidance for other countries' practices or international public policy making and identify possible priorities for the implementation of these practices.

The outline of this article is as follows. The next section is a literature review, followed by Section 3 describing the DEA models and the empirical data. The measurement of ELPI, test results and their implications are shown in Section 4. In Section 5, the article concludes limitations with suggestions for future research.

2. Literature Review

2.1. Green Logistics and Logistics Performance

The green supply chain is an increasingly hot topic in the field of management science, and green logistics is its branch. Environmental issues in logistics management and green supply chain processes have long been regarded as the main challenges facing European countries in the next millennium [16]. Generally speaking, logistics and freight transportation are important parts of the supply chain, which are related to the movement and storage of materials and products in the supply chain [17]. The aim of green logistics is to reduce the environmental externality of logistics operations and achieve the sustainable balance between economic, environmental, and social benefits [18].

The existing research on green logistics is mainly divided into two categories. One is macro level research, mainly attempting to improve the environmental friendliness of the global supply chain by means of supply chain coordination, logistics network design and optimization, emission control, and waste recovery. The other is micro-level research, focusing on the effect of a certain region, industry or enterprise in green practices, as well as the impact of green practices on economic benefits [19].

It is well known that freight transportation accounts for the largest share of logistics emissions. Therefore, transportation emission reduction practice, selection of transportation modes [20], and transportation network optimization are hot topics of green logistics. Lai and Wong [21] confirmed that green logistics management had a significant positive effect on improving environmental quality and manufacturer's business performance, while regulatory pressures promoted green logistics management and contributed to environmental profitability. Geiger [22] believed that communication technology played a role in promoting environmentally sustainable cargo transportation throughout Europe. By measuring the CO_2 emissions of container ships and their influencing factors in the past decade, Cariou Pierrea [23] found that the overall reduction in annual CO_2 emissions was mainly due to the general decline in speed and technological changes, but these positive effects were offset by an increase in total fleet capacity.

Based on LPI data of the World Bank, some scholars discussed their relationship with trade. Most of the existing literature used gravity models for analysis and their results tended to be consistent: There was a positive correlation between logistics performance levels and trade. Some scholars even equated the LPI index with trade facilitation. With the increasing attention to logistics environment issues, research in recent years has gradually paid attention to the relationship between LPI and the environment. Zaman [24] discussed the impact of the logistics performance index on economies of scale in European countries. Studies have shown that: the "timeliness" and "tracking and tracking commodities" of LPI significantly increased energy consumption, the "infrastructure" could improve renewable energy efficiency and reduced CO_2 emissions, while the "service" index could significantly increase CO_2 emissions. Khan and Qian li [25] examined the causal long-term relationship between environmental logistics performance indicators (ELPI) and growth-specific factors. The results show that per capita income, manufacturing and services account for the proportion of GDP which was affected by CO_2 emissions and greenhouse gas emissions. Logistics capabilities and infrastructure contributed to economic growth. The three different environmental logistics performance indicators (ELPI) in this study were represented by the interaction of the logistics performance index (LPI) with CO_2 emissions, fossil fuel energy consumption, and greenhouse gas emissions. Therefore, the ELPI proposed in this study was only economically meaningful. It is not an independent evaluation index, nor can it be internationally ranked. Liu and Yuan et al. [26] analyzed the nexus between logistics performance and environmental degradation using data obtained from 42 Asian countries between 2007 and 2016. The findings paralleled the studies of Zaman (2017) [24] that international shipments in logistics performance index (LPI) significantly decreased CO_2 emissions, while the timeliness of logistics significantly intensified the CO_2 emissions in Asian countries. In spite of this, the effect of green logistics practice was still not significant.

In sum, logistics performance is significantly related to the environment. The composite of new indices that combines environmental factors with LPI is theoretically supported. At present, there seems to be no perfect index to evaluate green logistics performance.

2.2. Data Envelopment Analysis

There are parametric and non-parametric methods to evaluate efficiency in mainstream literature. Stochastic frontier analysis (SFA) belongs to the parametric method. Its estimation results vary significantly due to the different functional forms selected, and the parametric method does not contain undesired output [27]. DEA is a nonparametric method for calculating the production frontiers of each decision-making unit (DMU) and the best performing DMUs in practice, and calculating the efficiency score of each DMU based on the distance between them. Charnes [28] proposed the original data envelopment analysis with constant return on scale (CCR-DEA). Subsequently, Banker [29] extended it to the DEA model with variable returns on scale (BCC-DEA). Because of its absolute advantages in processing multiple inputs and outputs, the DEA model was widely used in energy [30,31], industrial production, banking and finance [32,33], logistics [34–36], and other industries. Traditional CCR-DEA and BCC-DEA models are considered as radial models, assuming that all outputs should be maximized with given inputs. However, this assumption is inappropriate when undesired outputs (environmental factors) are produced as by-products of the desired output. To overcome this problem, Tone [37] proposed a non-radial measurement model based on relaxation (SBM-DEA). Zhou [38] incorporated unexpected outputs on the basis of this model and constructed two environmental performance indices based on the SBM model. Shi et al. [39] proposed an extended DEA model to evaluate China's industrial energy efficiency by taking the non-expected output as an input. Numerous research achievements show that DEA is a better method for evaluating environment-related efficiency [40].

The SBM model is used to try to avoid the relaxation problem and the choice of angle to solve the measurement problem of undesired output. However, it is unable to avoid the inherent shortcomings of directional distance function [15]: Due to the fact that the subjective direction vector is set, the same decision-making units in different direction vector sets under the condition of the efficiency of the calculation results are biased. Sueyoshi and Goto [15] proposed the environmental range adjusted measure (RAM) model based on research of Ref. [41]. This model is not only non-radial and non-angular, but also avoids subjectively setting model parameters, so as to effectively measure the efficiency including environmental factors [42]. At the same time, Sueyoshi further extended the RAM model to satisfy inter-temporal comparisons [43] and allow variables to be zero/negative values [44]. On these bases, it is suitable to calculate the environmental logistics performance index with a DEA-RAM model.

3. Methods and Data

In the RAM model, there are two concepts: natural disposability and managerial disposability. Natural disposability indicates that DMU can reduce the direction vector of its input and thus reduce the bad output direction vector. Then, with the input vector reduced, DMU tries to increase its good output directional vectors by as many as possible. Specifically, countries reduce carbon emission by reducing energy consumption, hence increasing environmental efficiency. This means that the desirable (good) outputs may be correspondingly reduced. As opposed to the concept of natural disposability, management disposability indicates that DMU increases its input direction vector to reduce the bad output direction vector. Then, given the added input vector, DMU tries to add as many good output direction vectors as possible [45]. This means that, given the same amount of energy, efficient countries can create more desirable (good) outputs or lower carbon emission intensity by improving energy efficiency and developing clean energy technologies. However, the current international environmental protection achievements are mainly based on energy conservation and emission reduction, rather than the application and promotion of clean energy technologies in transportation. In addition, clean energy consumption, such as electricity or natural gas, is not included in the input indicators. Therefore, this article uses the RAM model under natural disposability to measure the environmental logistics performance index of each country.

3.1. ELPI under natural disposability

Suppose there are n countries (DMU) in this study. Each country (DMU_j, j = 1, . . . , n) requires m inputs $X_j = (x_{1j}, \ldots, x_{mj})$, like energy, to generate s desirable (good) outputs $G_j = (g_{1j}, \ldots, g_{sj})$, like six components of LPI, and f undesirable (bad) outputs $B_j = (b_{1j}, \ldots, b_{hj})$, like CO_2 emissions. The RAM-DEA model under natural disposability is demonstrated as follows.

$$
\begin{aligned}
& \max \sum_{i=1}^{m} R_i^x d_i^x + \sum_{r=1}^{s} R_i^g d_i^g + \sum_{f=1}^{h} R_f^b d_f^b \\
& s.t. \sum_{j=1}^{n} x_{ij}\lambda_j + d_i^x = x_{ik}, i = 1, \ldots, m, \\
& \sum_{j=1}^{n} g_{rj}\lambda_j - d_r^g = g_{rk}, r = 1, \ldots, s, \\
& \sum_{j=1}^{n} b_{fj}\lambda_j + d_f^b = b_{fk}, f = 1, \ldots, h, \\
& \sum_{j=1}^{n} \lambda_j = 1, \\
& \lambda_j \geq 0, j = 1, \ldots n, d_i^x \geq 0, i = 1, \ldots, m, \\
& d_j^g \geq 0, r = 1, \ldots s, d_f^b \geq 0, f = 1, \ldots, h.
\end{aligned} \tag{1}
$$

Model (1) shows the formulations of the RAM-DEA model under natural disposability, wherein d_i^x (i = 1, ... ,m), d_r^g (r = 1, ... ,s), and d_f^b (f = 1, ... ,h) are all slack variables. $\overline{x_i} = \max_j\{x_{ij}\}$ and $\underline{x_i} = \min_j\{x_{ij}\}$ are defined as the upper and lower bounds of inputs for all i. The upper and lower bounds of the input and outputs determine the range R. The range for inputs becomes $R_i^x = 1/[(m+s+h)(\overline{x_i} - \underline{x_i})]$ for all i. Similarly, the range for desirable outputs becomes $R_r^g = 1/[(m+s+h)(\overline{g_r} - \underline{g_r})]$ for all r, and the range for undesirable output becomes $R_f^b = 1/[(m+s+h)(\overline{b_f} - \underline{b_f})]$ for all f.

The unified efficiency, which could be defined as an integrated environmental logistics performance index under natural disposability, could be measured by:

Environmental Logistics Performance Index =

$$
1 - \left(\sum_{i=1}^{m} R_i^x d_i^{x*} + \sum_{r=1}^{s} R_r^g d_r^{g*} + \sum_{f=1}^{h} R_f^b d_f^{b*} \right) \tag{2}
$$

All slack variables are determined by the optimality of Model (1), indicating the difference between the specific DMU and the benchmark under natural disposability. Equation (2) is obtained from the optimality of Model (1) [46]. We use Matlab software to run the model.

3.2. Data and Variables

Energy consumption and CO_2 emissions are the biggest determinants of environmental efficiency. It is noteworthy that CO_2 emissions from transport contain emissions from the combustion of fuel for all transport activity in any sector, except for international marine bunkers and international aviation. This includes domestic aviation, domestic navigation, road, rail and pipeline transport [47]. International marine bunkers and international aviation account for a small proportion of CO_2 emissions. According to the IEA's CO_2 emissions overview, water accounts for only about 10 percent of global transport CO_2 emissions [1]. In this respect, the statistical dimension of CO_2 emissions is acceptable. However, the emissions from fossil energy combustion are not only CO_2, but also other polluting gases such as nitrogen oxides. In 2014, shipping accounted for 2.5% of global greenhouse gas emissions, and these emissions are expected to increase by 50% to 250% [48]. From the perspective of environmental protection, energy conservation is more important than emission reduction, and CO_2 emissions from transport cannot systematically reflect the overall environmental performance of the transportation sector. Therefore, the energy consumption of transportation needs to be taken into consideration.

The majority of energy consumption of transportation is from oil, followed by natural gas and electricity. This article only considers oil consumption in transportation, because of the large amount of missing data of natural gas and electricity consumption. According to the statistics of IEA [49], transportation energy is mainly based on oil, and natural gas and electricity account for only 4.3% and 1.25% of their energy consumption, respectively. Therefore, it is acceptable to use oil consumption to represent the energy inputs of logistics and transportation. The data comes from the World Energy Statistics published by the International Energy Agency.

As shown in Figure 1, the natural logarithm of CO_2 emissions of transport is highly correlated with the natural logarithms of oil consumption of transport, and the adjusted R square is 0.823. Although there is a strong linear correlation between CO_2 emissions and oil consumption, they are not interchangeable. Combined with Tables 1 and 2, it can be preliminarily concluded that the addition of an energy consumption indicator significantly affects the ELPI scores of some countries, such as Venezuela, RB.

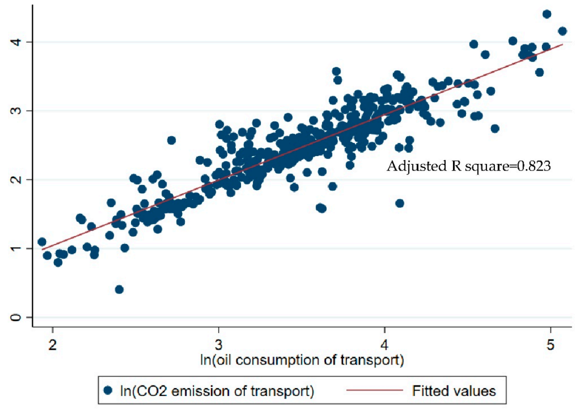

Figure 1. CO_2 emissions and oil consumption in transport.

CO_2 emissions from transport are highly correlated with GDP [14]. Due to the large differences in the economic development levels of countries around the world, it is unreasonable to directly use CO_2 emissions to reflect the environmental efficiency of transportation. Therefore, this article considers the CO_2 emission intensity, that is, the CO_2 emissions from transport per unit of GDP (constant 2010 US$)), as an undesired output indicator. Similarly, the intensity of oil consumption in transport (oil consumption in transport per unit of GDP) is used as an input. The setting of the intensity index can reduce the influence of heterogeneity on the measurement accuracy of a DEA model to a certain extent.

There were different views on the roles of the six components of the LPI in the input–output indicator system. All LPI were regarded as output indicators in some studies [14], while other studies divided LPI into inputs and outputs [13]. In this article, ELPI of the two cases are measured and compared. It is found that the correlation coefficient between scores of ELPI obtained by the first case and the total scores of LPI is the largest. Therefore, like the first case, this article considers all the six components of the LPI as output indicators.

Another issue worth pointing out is that the energy consumption and CO_2 emissions used in the article are the total transport data, including international and domestic transport, while LPI is primarily used to measure international logistics. We know that both international logistics and domestic logistics share services and infrastructure to a certain extent. Moreover, some international logistics businesses need close cooperation with domestic logistics, such as multimodal transport. In this sense, LPI can reflect a country's overall logistics performance level, not just international logistics performance.

In the environmental logistics performance index (ELPI), eight variables are used: one input and seven outputs. The input is the intensity of oil consumption from transportation. Six of the desirable outputs correspond to the six components of the LPI. The undesirable output is the intensity of CO_2 emissions from transportation. The years of sample selection are 2007, 2010, 2012, and 2014. Some countries have been eliminated because of large amount of missing data. One-hundred-and-twelve countries remain in the sample.

It is worth pointing out that the input indicator of energy consumption alone cannot be regarded as a comprehensive evaluation of the environmental-economic efficiency of the transportation. The purpose of this article is to use DEA technology to combine energy consumption and carbon emissions data with LPI into a new index. This index is an assessment of the logistics performance of each country considering environmental factors under the assumption that other inputs are equivalent. This measure is used in the absence of data.

According to the preliminary statistics of the data, the United States has been the world's biggest oil consumer in transport during the study period, followed by China, Japan and India. The rank of transportation oil consumption intensity (the ratio of transportation oil consumption to GDP) has changed dramatically compared to oil consumption, with Togo, Benin and Kyrgyz Republic in the top three. Singapore's oil consumption intensity has been at the lowest level for 4 years, followed by Hong Kong SAR (China), Switzerland and Norway; United States and China are at an intermediate level. For the countries included in the study, their transport sectors rank similarly in CO_2 emission intensity to oil consumption intensity, except Venezuela, RB and Uzbekistan. The representative data and descriptive statistics of input–output variables used in this article in 2014 are shown in Table 1. It is sorted by the scores of the first component of the LPI (Customs) in the table.

Table 1. Description of input–output variables in 2014.

Country	Six Components of LPI Scores						CO_2 Emission		Oil Consumption			
	Cust	*Infra*	*Serv*	*Ship*	*Track*	*Time*	*Intensity (kg Per 2010US$ of GDP)*	*Rank*	*Intensity (Tonnes Per Million USD)*	*Rank*	*Total (Thousands Tonnes)*	*Rank*
The Top 10%												
Norway	4.21	4.19	4.19	3.42	3.50	4.36	4.13	106	8.81	109	4399	50
Germany	4.10	4.32	4.12	3.74	4.17	4.36	4.22	105	12.74	102	49,574	8
Singapore	4.01	4.28	3.97	3.70	3.90	4.25	2.99	110	6.93	112	2159	66
Netherlands	3.96	4.23	4.13	3.64	4.07	4.34	3.90	107	10.81	107	9506	30
United Kingdom	3.94	4.16	4.03	3.63	4.08	4.33	4.52	102	12.33	104	37,271	13
New Zealand	3.92	3.67	3.56	3.67	3.33	3.72	9.56	76	22.35	82	4492	47
Switzerland	3.92	4.04	3.75	3.58	3.79	4.06	2.53	111	7.70	110	5459	40
Finland	3.89	3.52	3.72	3.52	3.31	3.80	4.57	101	12.70	103	3463	56
Australia	3.85	4.00	3.75	3.52	3.81	4.00	6.97	90	20.07	91	29,398	15
Luxembourg	3.82	3.91	3.78	3.82	3.68	4.71	10.83	67	29.81	59	1977	71
Japan	3.78	4.16	3.93	3.52	3.95	4.24	3.60	108	13.91	99	67,456	4
United States	3.73	4.18	3.97	3.45	4.14	4.14	10.83	66	30.87	53	538,060	1
Hong Kong SAR (China)	3.72	3.97	3.81	3.58	3.87	4.06	2.45	112	7.15	111	2085	67
Canada	3.61	4.05	3.94	3.46	3.97	4.18	9.57	66	29.92	59	53,828	7
China	3.21	3.67	3.46	3.50	3.50	3.87	10.62	70	22.83	79	239,278	2
The bottom 10%												
Benin	2.64	2.35	2.35	2.69	2.45	2.85	49.80	2	127.12	1	1234	86
Jordan	2.60	2.59	2.94	2.96	2.67	3.46	26.18	9	63.6951	6	2282	64
Colombia	2.59	2.44	2.64	2.72	2.55	2.87	9.94	72	23.86	78	9026	31
Venezuela, RB	2.39	2.61	2.76	2.94	2.92	3.18	6.61	94	31.6901	49	15,286	22
Russian Federation	2.20	2.59	2.74	2.64	2.85	3.14	16.23	30	28.15	63	58,090	6
Togo	2.09	2.07	2.14	2.47	2.49	2.60	52.80	1	93.47	3	419	107
Kyrgyz Republic	2.03	2.05	2.13	2.43	2.20	2.36	45.53	3	100.16	2	748	98
Tunisia	2.02	2.30	2.42	2.91	2.42	3.16	15.33	36	42.15	32	2006	70
Gabon	2.00	2.08	2.25	2.58	1.92	2.31	6.92	91	14.30	98	260	111
Myanmar	1.97	2.14	2.07	2.14	2.36	2.83	12.04	58	33.52	46	2194	65
Kenya	1.96	2.40	2.65	3.15	3.03	3.58	15.26	38	33.62	45	2066	68
Sudan	1.87	1.90	2.18	2.23	2.42	2.33	13.12	51	30.32	55	2491	58
Cameroon	1.86	1.85	2.52	2.20	2.52	2.80	11.86	60	29.71	60	1038	91
Uzbekistan	1.80	2.01	2.37	2.23	2.87	3.08	13.42	49	21.07	88	1329	84
Yemen, Rep.	1.63	1.87	2.21	2.35	2.21	2.78	27.20	8	54.45	14	2354	62
Summary statistics												
Min	1.63	1.85	2.07	2.08	1.92	2.31	2.45		6.93		255	
Max	4.21	4.32	4.19	3.82	4.17	4.71	52.80		127.12		538,060	
Ave	2.87	2.94	3.02	3.03	3.08	3.42	13.89		34.16		16,747.42	
S.D.	0.61	0.67	0.57	0.44	0.55	0.57	9.01		19.41		56,501.99	

Source: The World Bank; the World Energy Statistics published by the International Energy Agency. Note: "Cust", "Infra", "Serv", "Ship", "Track", "Time" represent the six components of LPI's Customs, Infrastructure, and Services, International shipments, Tracking and tracing and Timeliness, respectively.

4. Results and Discussion

In this section, we discuss the ranking differences and inter-group heterogeneity of ELPI scores across countries. One-way analysis of variance and the Kruskal-wallis test are used to test whether there are significant differences between income and region groups.

4.1. Environmental Logistics Performance Index Scores and Ranks

Table 2 respectively summarizes the ELPI scores of the top and bottom 20% countries in the world, sorted by the weighted ELPI. It shows that there are 12 countries that display efficient ELPI for at least 1 year during our study period. We notice that among these countries, Hong Kong SAR (China), Singapore, and Netherlands maintain efficiency over the whole study period. Germany, Denmark, Sweden and other countries follow closely behind them and perform well. The efficient ELPI means that these countries perform best in international logistics practices and green transportation in a specific year.

According to the PPP-GNI 9 index elaborated by the World Bank, the top 20% countries in ELPI are considered as high-income countries. By contrast, most of the bottom 20% countries are groups of low income or lower-middle income countries from Sub-Saharan Africa or South Asia. The ranking of the environmental logistics performance index seems to be closely related to income or region.

Table 2. Ranks of ELPI.

Country	ELPI						WLPI
	2007	2010	2012	2014	WAve	Rank	Rank
The top 20%							
Hong Kong SAR (China)	1.000	1.000	1.000	1.000	1.000	1	8
Netherlands	1.000	1.000	1.000	1.000	1.000	1	3
Singapore	1.000	1.000	1.000	1.000	1.000	1	2
Germany	0.961	1.000	1.000	1.000	0.997	4	1
Denmark	0.904	0.916	1.000	1.000	0.982	5	13
Sweden	0.953	1.000	0.906	1.000	0.972	6	6
Belgium	0.895	0.950	0.942	1.000	0.971	7	4
Switzerland	0.945	1.000	0.897	1.000	0.969	8	14
Norway	0.887	1.000	0.855	1.000	0.954	9	11
United Kingdom	0.929	0.945	0.918	0.966	0.948	10	5
Luxembourg	0.744	1.000	0.860	1.000	0.945	11	10
Japan	0.939	0.954	0.934	0.946	0.943	12	7
France	0.859	0.906	0.902	0.907	0.902	13	15
United States	0.841	0.880	0.924	0.896	0.898	14	9
Ireland	0.903	1.000	0.793	0.913	0.892	15	18
Finland	0.876	0.919	1.000	0.832	0.891	16	17
Canada	0.872	0.890	0.881	0.880	0.881	17	12
Australia	0.846	0.895	0.855	0.881	0.873	18	16
Austria	0.942	0.879	0.925	0.834	0.872	19	19
Italy	0.800	0.837	0.842	0.852	0.844	20	21
China	0.683	0.763	0.774	0.778	0.769	26	26
The bottom 20%							
Colombia	0.458	0.528	0.568	0.477	0.507	63	73
Ghana	0.311	0.391	0.415	0.419	0.407	91	91
Angola	0.445	0.339	0.368	0.435	0.405	92	101
Uzbekistan	0.249	0.493	0.418	0.389	0.401	93	99
Cameroon	0.446	0.436	0.448	0.351	0.395	94	104
Niger	0.294	0.427	0.480	0.353	0.393	95	98
Tanzania	0.314	0.454	0.472	0.341	0.389	96	100
Cambodia	0.377	0.292	0.389	0.412	0.388	97	84
Moldova	0.314	0.384	0.337	0.417	0.384	98	92
Gabon	0.365	0.417	0.409	0.351	0.376	99	110
Tajikistan	0.315	0.400	0.369	0.377	0.374	100	105
Algeria	0.262	0.329	0.371	0.393	0.370	101	93
Nepal	0.352	0.313	0.280	0.423	0.366	102	106
Mozambique	0.356	0.323	0.590	0.254	0.360	103	97
Myanmar	0.233	0.392	0.419	0.329	0.355	104	109
Bolivia	0.285	0.354	0.415	0.327	0.351	105	94
Yemen, Rep.	0.310	0.390	0.512	0.252	0.343	106	102
Haiti	0.314	0.432	0.274	0.318	0.321	107	111
Mongolia	0.240	0.302	0.320	0.332	0.318	108	108
Sudan	0.499	0.308	0.298	0.303	0.315	109	112
Benin	0.250	0.348	0.401	0.244	0.300	110	79
Togo	0.204	0.246	0.312	0.191	0.232	111	103
Kyrgyz Republic	0.217	0.317	0.180	0.166	0.193	112	107
Total Average	**0.550**	**0.597**	**0.600**	**0.604**	**0.598**		
Std. Dev.	**0.215**	**0.209**	**0.200**	**0.216**	**0.205**		

Notes: WAve is the abbreviation for weighted average, WLPI means the weighted LPI. Source: Own elaboration.

In order to facilitate a comparison with LPI's rankings of 112 countries, we obtain a composite index by weighting the annual ELPI scores. The annual scores are all weighted by the same weights as LPI: 6.7% in 2007, 13.3% in 2010, 26.7% in 2012, and 53.3% in 2014 [5]. This gives the highest weight to the latest data. Table 2 also demonstrates the rankings of the weighted ELPI (WELPI) and weighted LPI (WLPI). Overall, the weighted ELPI and weighted LPI rankings are similar. The absolute difference between the rankings of WELPI and WLPI is 4.526, and the variance is 4.601. From the ranking difference between ELPI and LPI, only 12.5% of the countries have ranking difference greater than 10.

The country with the biggest ranking difference between weighted ELPI and weighted LPI is Benin. Benin's weighted ELPI is 31 places lower than weighted LPI. Benin's LPI scores are at the lower-middle level, and its ELPI scores ranking significantly decline due to its high carbon intensity and high energy intensity. According to the statistical results of Table 1, Benin's carbon intensity and oil consumption intensity are the second and first, respectively. It implies that Benin's performance of green transportation is worse than that of LPI. Therefore, in order to improve the performance of ELPI, Benin should focus on improving energy efficiency and reducing carbon intensity in the transportation sector and upgrading the level of logistics development. Other countries with big differences between weighted ELPI and weighted LPI rankings are Jordan and Venezuela, RB. Jordan's situation is similar to that of Benin. Venezuela, RB's weighted ELPI score is 16 places higher than its weighted LPI. Its higher performance score in ELPI is mainly a benefit from its low carbon emission intensity. It can be seen in Table 1 that Venezuela, RB's carbon emission intensity is ranked 94^{th}, ranking lower than many high-income countries.

4.2. Analysis and Tests

Spearman's correlation coefficient is used to estimate the pairwise correlation between WELPI, WLPI and Mariano's LCLPI [14]. As shown in Table 3, we can conclude that there is a strong correlation between WLPI and WELPI. This shows that ELPI's ranking results generally match the LPI. ELPI's rankings fluctuate in the rankings of LPI, reflecting the fact that green transportation levels in these countries are above or below their LPI levels.

Table 3. Tests of significance.

	WLPI	LCLPI		WELPI	
LCLPI(Mariano, 2017)	0.0356	1.0000 ***		——	
WELPI	0.9853 ***	0.0354		1.0000 ***	
Responsible variable	Factor variable	Sum Sq.	Df	Mean Sq.	F value
WELPI	Between groups	2.922	3	0.9739	59.47 ***
	Within groups	1.768	108	0.016	

Notes: *** represent the significance level of 1%; WELPI means the weighted ELPI.

By analyzing the bottom 20% and the top 20% performers, we find that the environmental logistics performance index (ELPI) appears to be related to income and region. One-way analyses are used to test for significant differences in income. Table 3 shows the results of the test, which suggest that the null hypotheses, i.e., the average performance of the ELPI is independent of income, and are rejected at the significance level of 1%. This result indicates that the ELPI is significantly different from other groups in at least some income groups, but it does not mean there are significant differences between all groups.

To further understand the differences between the groups, we calculate the average ELPI scores for each income group during 2007–2014 and illustrate this in graph i of Figure 2. Obviously, the average ELPI scores have differences and hierarchy in income. High-income countries are significantly higher than others, followed by upper-middle-income countries. In terms of average ELPI scores, the average ELPI scores of each income group have maintained a certain degree of growth during the study period, except for low income countries, which declined in 2014. In recent years, countries around the world have become more and more inclined to slow down the carbon agenda and have achieved certain success. Therefore, their ELPI scores keep increasing under natural disposability. However, low-income countries pay insufficient attention to emissions reductions, and the gap with other countries has gradually increased.

Figure 2. Average ELPI scores grouped by income and region.

According to Arvis's survey [5], the demand for sustainable transportation in high-income countries is growing. Moreover, developed countries are more capable of promoting the greening of transportation. Consequently, the gap between their ELPI scores and those of other countries gradually widened. The difference in average scores between low-income countries and lower-middle-income countries is not obvious, and they have the lowest ELPI. These countries are considered to be lagging in the development of logistics infrastructure and services, and ignoring environmental protection in transport management [5].

Similarly, the annual average ELPI scores are calculated in region groups during 2007–2014, to analyze whether there is a significant difference in ELPI scores in each regional group. As shown in graph ii of Figure 2, the average scores of ELPI have significant hierarchical differentiation in each region. It is worth noting that the gap in average ELPI scores across all regions narrowed in 2014, except for Sub-Saharan Africa.

The Kruskal-Wallis ranking sum test is a useful test for deciding whether k independent samples come from different regions groups. Multiple comparisons between groups help us to know the difference between the two groups. Table 4 suggests that the null hypothesis, i.e., East Asia & pacific and Latin American & Caribbean countries come from identical populations with the same median of ELPI, may be rejected at the significance level of 1%. It can be seen that there are no significant differences in most of ELPI scores between Sub-Saharan Africa, Middle East & North Africa, and South Asia and Latin American & Caribbean. This means that these regions belong to the same level. Similarly, East Asia & Pacific and Europe & Central Asia can be classified at the same level, while North America is significantly different from other regions.

Table 4. Kruskal-Wallis Test and Multiple comparisons between groups.

	WELPI
Kruskal-Wallis Test (H statistic)	32.41 ***
Multiple comparisons between groups (rank means difference)	
East Asia & pacific/Europe & Central Asia	0.16
East Asia & pacific/Latin American & Caribbean	24.33 **
East Asia & pacific/Middle east & North Africa	28.23 **
East Asia & pacific/Sub-Saharan Africa	43.53 **
East Asia & pacific/South Asia	31.82 **
East Asia & pacific/North American	27.43
Europe & Central Asia/Latin American & Caribbean	24.49 ***
Europe & Central Asia/Middle east & North Africa	28.39 ***
Europe & Central Asia/Sub-Saharan Africa	43.69 ***
Europe & Central Asia/South Asia	31.97 **
Europe & Central Asia/North American	27.28
Latin American & Caribbean/Middle east & North Africa	3.90
Latin American & Caribbean/Sub-Saharan Africa	19.20 **
Latin American & Caribbean/South Asia	7.49
Latin American & Caribbean/North American	51.76 **
Middle east & North Africa/Sub-Saharan Africa	15.30
Middle east & North Africa/South Asia	3.58
Middle east & North Africa/North American	55.67 ***
Sub-Saharan Africa/South Asia	11.72
Sub-Saharan Africa/North American	70.97 ***
South Asia/North American	59.25 **

Notes: *** and ** respectively represent the significance level of 1% and 5%. Source: Own elaboration.

In summary, North America can be classified as a high-performance region, East Asia & Pacific and Europe & Central Asia as medium-performance regions, while Sub-Saharan Africa, Middle East & North Africa and South Asia and Latin American & Caribbean are low-performance regions.

It should be noted that many countries in Europe & Central Asia have higher ELPI scores than those in North America. Their average level is pulled down by some inefficient countries in the region.

4.3. Potentials for Reduced Oil Consumption Intensity and Emission Intensity

According to the RAM-DEA model theory, the slacks of input or output variables are utilized to measure the gap between the DMU's variables and benchmarks. Inefficient countries can improve efficiency by adjusting their inputs and outputs to reach the benchmarks. Therefore, the slack of each variable can be regarded as the potential for improvement of this variable. For example, under natural disposability, d_x and d_b in Model (1) can be regarded as the theoretical maximum potential for oil consumption intensity reduction and carbon intensity reduction of each country, respectively.

Table 5 documents the top 10% of countries and other representative countries for the reduction potential of oil consumption intensity and carbon intensity during the study period (sorted by the oil consumption intensity reduction potential in 2014). It can be seen from Table 5 that Benin has the highest oil consumption intensity reduction potential in 2014, followed by Togo and Kyrgyz Republic. Six countries have the theoretical maximum oil consumption intensity reduction potential of more than 50 tons per million USD in 2014. These countries are mainly low-income countries from low performance regions. According to the statistical analysis of the above results, there is a significant negative correlation between reduction potential and ELPI scores. It seems that higher-income groups have lower reduction potential.

Table 5. Oil consumption intensity and carbon intensity reduction potential.

	Oil Consumption Intensity Reduction Potential (Tons Per Million USD)				Carbon Intensity Reduction Potential (kg Per 2010 US$ of GDP)			
Year	**2007**	**2010**	**2012**	**2014**	**2007**	**2010**	**2012**	**2014**
Benin	114.53	130.42	125.09	114.38	43.83	46.54	48.39	45.59
Kyrgyz Republic	119.41	119.16	137.49	87.42	43.57	39.32	79.76	41.31
Togo	127.87	145.56	110.56	80.73	33.62	59.68	53.21	48.58
Cambodia	75.90	76.46	69.68	62.52	17.84	25.68	26.83	24.40
Moldova	95.08	82.10	68.70	59.41	14.03	14.37	14.74	13.01
Jordan	84.44	50.38	57.08	50.95	23.91	17.83	24.27	21.96
Algeria	49.19	45.17	42.51	49.38	22.29	20.14	22.46	23.83
Malaysia	59.31	41.47	44.66	49.37	17.25	15.57	15.63	18.74
Bolivia	82.83	59.02	52.42	46.17	27.87	26.22	30.50	29.73
Ghana	44.85	36.66	39.00	46.10	15.76	10.89	13.57	13.68
India	28.37	21.77	27.37	22.39	10.33	8.12	11.04	7.85
United States	26.69	21.12	20.37	18.13	10.72	6.96	7.32	6.61
Canada	23.07	18.10	21.21	17.18	9.05	6.20	7.43	5.35
Russian Federation	27.46	21.63	17.58	15.41	15.17	13.16	14.61	12.02
Brazil	23.19	9.90	16.35	14.63	6.70	4.27	7.33	5.56
Colombia	20.26	8.89	12.99	11.12	8.02	5.24	8.49	5.72
China	33.06	15.73	16.47	10.09	9.91	6.52	9.05	6.40
New Zealand	20.58	15.79	17.16	9.61	8.35	5.38	7.38	5.34
Angola	9.01	10.61	6.57	8.39	10.33	10.58	12.35	10.94
Australia	19.90	13.13	10.87	7.33	6.06	3.71	5.26	2.75
Japan	4.96	1.12	3.59	4.11	2.51	0.00	1.59	0.00
Austria	7.99	6.67	6.52	3.00	4.50	1.59	1.90	1.03
Italy	5.86	2.44	8.45	2.77	4.35	0.98	2.75	0.95
Gabon	1.63	0.00	5.88	1.56	4.94	3.61	5.24	2.71
Ireland	3.59	0.00	8.10	0.87	4.55	0.00	2.28	0.13
Belgium	6.75	3.32	8.65	0.00	3.96	0.84	2.92	0.00
Luxembourg	32.20	0.00	29.11	0.00	11.20	0.00	10.36	0.00
Switzerland	0.37	0.00	0.66	0.00	1.25	0.00	0.44	0.00
United Kingdom	1.82	1.74	6.39	0.00	3.72	0.65	2.42	0.39
Sweden	3.78	0.00	4.62	0.00	3.45	0.00	2.61	0.00
Norway	0.00	0.00	1.08	0.00	2.53	0.00	2.01	0.00

However, there are some exceptions. Among the bottom 20% of countries in ELPI, Gabon, an upper-middle income country in Africa, has the lowest oil consumption intensity reduction potential, followed by Angola. Gabon's oil consumption intensity reduction potential is less than 2 tons per million USD, which is lower than some high-income countries such as New Zealand and Australia. Among the top 20% countries in ELPI, United States has the greatest oil consumption intensity reduction potential, followed by Canada. Their reduction potential exceeds that of inefficient lower-middle-income countries such as Russia Federation, Brazil and China. Countries such as Sweden and Norway had zero oil consumption intensity reduction in 2014, because they were efficient in ELPI this year, and the oil consumption intensity reduction potential of other high-income countries are largely zero. The ranking results for the oil consumption intensity reduction potential rate (oil consumption intensity reduction potential/energy consumption intensity [50]) and oil consumption intensity reduction potential are the same. The oil consumption intensity reduction potential rate of Gabon is also higher than that of United States, Russia and other countries. The above results indicate that countries with high oil consumption intensity have high oil consumption intensity reduction potential and usually have low ELPI scores. These countries should pay more attention to the energy consumption control to reduce energy redundancy and thus improve ELPI.

Similarly, Table 5 also records the results of theoretical maximum carbon intensity reduction potentials of representative countries during the study period. The countries with the greatest potential for carbon intensity reduction are Togo, followed by Benin and Kyrgyz Republic, whose carbon intensity reduction potential is above 40 kg per GDP. Most of these countries belong to sub-Saharan Africa. In general, countries with great oil consumption intensity reduction potentials also have big potentials to reduce carbon intensity. Among the top 20% countries in ELPI, United States has the greatest potential to reduce carbon intensity, followed by Canada and Australia, while most of the others have zero carbon intensity reduction potential.

In summary, low-income countries and Sub-Saharan African countries have the worst performance in international logistics and green transportation and have the greatest reduction potential for oil consumption intensity and carbon intensity in transportation. If we would like to improve the overall environmental logistics performance level of the world and promote the sustainable development of transportation and society, low income countries and Sub-Saharan Africa should be regarded as the primary targets for improvement.

Sub-Saharan Africa has always been the poorest area of concern to the World Bank. Sub-Saharan Africa's infrastructure network is increasingly lagging behind other developing countries. It is characterized by a lack of regional linkages [51]. Having received significant capital and attention to potential infrastructure development over the past few years, Sub-Saharan Africa's huge supply shortages have been addressed [52]. However, according to this article, their logistics and transportation development did not achieve the expected results, and the gap with other regions is expanding. The New Structural Economics School questioned the effectiveness of aid projects in Africa. They argue that "shock-based therapy" that mimics developed countries does not apply to developing countries. Following the successful case of Ethiopia, the new structural economics are more convinced that reform and development should be carried out systematically according to the country's resource endowment [53]. Their development ideas may also apply to the logistics and transportation industry. The sustainable development of the logistics industry can only be promoted by improving transportation environment management measures systematically according to the country's resource endowment while developing infrastructure. According to the IEA's report [1,3], road transport has the greatest proportion of energy consumption and carbon emissions. Therefore, an important breakthrough in improving ELPI is to guide and facilitate the transfer of freight demand for road transport to other environmentally friendly modes of transport.

Although ELPI scores are related to income and region, income or region alone cannot explain the differences in ELPI performance across countries. The above exception countries indicate that the level of development of logistics performance and green transportation can outperform or fall behind their income or regional group peers. It can be seen that it is necessary to assess the country's environmental efficiency by industry, which is more conducive to discovering the shortcomings of its environmental protection.

5. Conclusions

In this article, we use RAM method of DEA to construct a composite index, ELPI. We analyze the differences of ELPI scores and discuss the potentials for reduction in oil consumption intensity and carbon intensity of representative countries. The main finding of this study is that ELPI scores have a significant relationship with income and region. Low-income countries and Sub-Saharan Africam countries have the worst performance in ELPI. ELPI scores have a distinct three-level stratification between regional groups, but the gap between their levels is gradually narrowing. On the other hand, the gap between high-income countries and other income groups is gradually increasing. Another important finding is that countries with lower ELPI scores tend to have higher oil consumption intensity and carbon intensity reduction potentials. Furthermore, ELPI has a strong positive correlation with LPI. This index is improved on existing research, with more reasonable and interpretable ranking results, and it can be used as an auxiliary index of LPI.

As can be seen from the article, the way to improve ELPI is to achieve green transportation while improving LPI. It is agreed that promoting the use of clean energy and changing transportation structures are feasible ways to achieve green transportation. Although the economic development and carbon emissions are still not completely decoupled, the results of this study make us believe that logistics performance and green transportation can achieve a win-win situation by strengthening environmental regulations and promoting clean energy use. In other words, countries with excellent LPI also perform well in green transportation. This provides theoretical support for government management and environmental policy.

Malmquist productivity index can be used to analyze technological advances and catch-up effects of each country in ELPI. Limited by data, the transportation data used in this article included passenger and freight, while passenger transport is not related to LPI. In addition, ELPI in this article is used to measure the green level of total transport including domestic and international transport, while LPI is primarily used to measure international logistics. Therefore, the current ranking of ELPI is indicative. In the future, we will try to optimize the environmental logistics performance index through optimization of data sets or decomposing the environmental efficiency of passenger and freight transportation.

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