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Determining Productivity of Container Ports and Climate-Change Factors using a Hybrid of Malmquist Productivity Index and Artificial Neural Network

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Abstract
Assessing port productivity enables each port to understand its competitive advantages and disadvantages. Hence, the objectives of this research were: (1) to assess the productivity levels of ten container ports in Malaysia, and (2) to determine important climate change factors on the productivity levels of container ports. The findings show that Port of Tanjung Pelepas exhibits the highest productivity index, followed by Port Klang and Port of Penang. Further results also revealed that the productivity of container ports was most impacted by sea level, followed by precipitation level, wind speed, and temperature.

Keywords: Productivity; Malmquist Productivity Index; Climate Change Factors; Artificial Neural Network; Container Ports

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1.0 Introduction

Container ports are one of the most essential components of the Malaysian economy, as they, along with agriculture and tourism, are key contributors to the country's economic growth. According to Container Port Productivity (2022), port facilities are the key component in the country's development, as the exact number of containers was recorded, which is 28.3 million twenty-four equivalent units of container ships in 2021. The value of cargos managed in Malaysia is RM 480 billion, accounting for approximately 40% of Malaysia's foreign trade. The Port of Tanjung Pelepas in Johor and Port Klang in Selangor have achieved enormous success in recent years. These ports were nominated among the world's busiest, with Port Klang and Port Tanjung Pelepas ranked 12th and 15th, respectively (David, 2022).

Container ports' operations in Malaysia have been running efficiently, especially for major ports, since the government's move to privatize them in the 1990s. With the government's expansion of ports, container handling in major ports becomes more complex, as problems such as port congestion, operational delays, and inadequate infrastructure can occur. These difficulties can result in longer response times, more expenses, and worse service quality. As a result, there is an urgent need to measure and evaluate the productivity of sea container ports precisely. Assessing productivity enables stakeholders to identify inefficiencies, evaluate performance, and implement strategic improvements that enhance operational efficiency, reduce costs, and foster long-term growth in the marine trade.

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The measurement of productivity level assumes that controlled elements can determine it; nevertheless, environmental factors, such as natural phenomena, can also affect the performance of container ports. Regarding climate-related impacts, ports are highly vulnerable because even minor delays can result in billions of dollars in economic losses. In recent decades, ports have frequently suffered substantial damage along coastlines because of extraordinary storm events (Gavurova, 2018). Few studies (Song et al., 2013; Honma & Hu, 2014) have investigated the impact of environmental factors on the productivity of Malaysian container ports. As a result, it is crucial to understand the major environmental elements so that their impact can be effectively utilized for proper future management.

2.0 Literature Review

2.1 Productivity Measurement

Productivity is crucial to a country's economic prosperity. Specifically, productivity is determined by comparing the actual production volume to the production frontier. Numerous studies have been conducted to assess productivity across diverse industries. However, the literature about the maritime industry, specifically container port operators in developing nations, remains relatively scarce. Several scholars investigated the productivity of container ports using Data Envelopment Analysis (DEA) in conjunction with other approaches. For example, Song et al. (2013) evaluated the efficiency of container port terminal operators using the DEA Malmquist and the Epsilon-Based Measured (EBM) Model. The Malmquist model is employed to evaluate the overall rates of productivity growth in organizations and to perform decomposition analysis. Conversely, the EBM model provides efficiency and inefficiency scores for individual companies. The dataset comprised fourteen leading Vietnamese container ports and spanned the period from 2015 to 2020. It comprises the following four components: operating expense, total assets, owner's equity, and liabilities. The revenue and profit are the output. According to Song et al. (2013), the Malmquist model's integrated framework is practical and suitable for evaluating various subjects, and the EBM method has also been successfully applied.

Meanwhile, Ng and Lee (2007) evaluated the productivity of six container ports in Malaysia using the Data Envelopment Analysis (DEA) approach, which involves two models: the DEA-CCR and the DEA-BCC. Their results showed that Port Tanjung Pelepas (PTP) and Johor Port had the best performance compared to the other ports. This observation has confirmed PTP's place in the world ranking, while they also found that Westport and Northport did not perform well. In this analysis, a comparison was also conducted between Malaysian ports and Singapore ports, which shows that Singapore's ports are the best references, as they have the best port performance.

2.2 Hybrid Approaches

In their study, Honma and Hu (2014) employed a combination of Malmquist and an Artificial Neural Network (ANN)-based decision system to measure the energy efficiency of ship operations and to find out energy efficiency determinants, including ship speed, RPM, mean draught, trim, cargo quantity, wind, and sea effects. Marine environments and environmental factors affected fuel ships in container ports. Another study by Moghanlo et al (2021) analyzed the impact of climate change on the dust phenomenon. This study analyzed Zanjan Province in northwest Iraq using two representative concentration pathways (RCP) scenarios using Artificial Neural Networks (ANNs). In recent years, the winds in Zanjan Province have had a significant impact on the region, resulting in an increase in the number of dusty days in that area. That could have had numerous consequences, such as diseases and pollution. The researchers noted that understanding the extent of their changes was a crucial measure to minimize adverse effects. This study examined the influence of environmental factors on the dust phenomenon in Zanjan Province under two scenarios: RCP 2.6 and RCP 8.5. Using the ANNs, this study predicted the PM10 air pollution index from 2012 to 2050. The results show that the concentration of this pollutant increased in both scenarios. They mentioned that using ANNs is an effective tool in stimulating the dust phenomenon.

3.0 Methodology

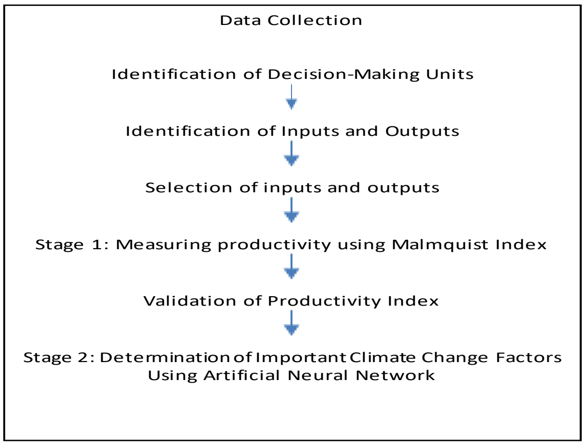

Figure 1: Research Flow Chart

This study employs a two-part methodology, as shown in Figure 1. The first stage involves determining the productivity level of the 10 ports in Malaysia, and the second stage involves identifying the environmental factors that could affect the productivity level of these ports in Malaysia. Before proceeding to the first step, several selections must be made to determine which inputs and outputs are appropriate for the study. The isotonicity and normalcy tests must be passed during the selection procedure.

The first stage is to assess the productivity using the Malmquist Productivity Index. Productivity is a crucial concept in economic development, and the transition from moderate to long-term growth is contingent upon the outlook for productivity growth. It is a crucial indicator of short-term economic dynamics. An increase in productivity is characterized by a transformation in the production function, which in turn affects the relationships between output and input. The productivity formula is written in Equation (1).

$$Total\ productivity = \frac{output\ quantity}{Input\ quantity} \tag{1}$$

The Malmquist Productivity Index (MPI) is a quantitative index developed by Professor Sten Malmquist, whose principles form the basis of the MPI. It is used to quantify productivity. This approach calculates the relative performance of a decision-making unit (DMU) over time using the technology of a base period. The distance of a particular production unit (container port) from a specified border, which comprises the highest-performing units of production, is utilized to determine its efficacy.

According to Suzuki and Nijkamp (2016), MPI is a measure that shows how much productivity has grown between two time periods, which they describe as better efficiency compared to a certain frontier. The measure of efficiency, or distance to the frontier, is calculated by assuming that the efficiency was calculated simultaneously with respect to the border, t. In the next period, *t+1,* of efficiency measure would be $d^{t+1}(x^{t+1}, y^{t+1})$. It is possible to measure efficiency based on a frontier from the previous or next time, as the efficiency score would be represented as $d^{t}(x^{t+1}, y^{t+1})$ or $d^{t+1}(x^{t}, y^{t})$, respectively. When the efficiency score for $d^{t}(x^{t}, y^{t})$ and $d^{t+1}(x^{t+1}, y^{t+1})$ cannot be greater than 1, while the $d^{t}(x^{t+1}, y^{t+1})$ and $d^{t+1}(x^{t}, y^{t})$. The productivity value can surpass 1 in the event of technological advancements or technological regressions. The MPI is utilised to quantify the productivity change between period t and t+1 by employing the productivity frontier from period t as a reference point. This index serves to assess and compare the efficiency and effectiveness of production processes across time and is expressed as

$$MP(x^{t}, y^{t}, x^{t+1}, y^{t+1}) \frac{d^{t}(x^{t+1}, y^{t+1})}{d^{t}(x^{t}, y^{t})} \tag{2}$$

According to Equation (2), the subscript "v" represents the variable return to scale (VRS) frontier, whereas the subscript "c" represents the constant return to scale (CRS) frontier. From the Equation (2)**Error! Reference source not found.**The interpretation of growth or decline according to productivity measures is irrelevant. Three of the components represent each part of the formulae, where:

$$Efficiency\ Change\ Index\ (EC)\ = \frac{d_v{}^{t+1}(x^{t+1}, y^{t+1})}{d_v{}^{t}(x^{t}, y^{t})} \tag{3}$$

$$Technical\ Change\ Index\ (TC) = \left[\frac{d_c{}^{t}(x^{t}, y^{t})}{d_c{}^{t+1}(x^{t}, y^{t})} \times \frac{d_c{}^{t}(x^{t+1}, y^{t+1})}{d_c{}^{t+1}(x^{t+1}, y^{t+1})}\right] \tag{4}$$

The second phase of the study involved examining environmental conditions and their impact on container port productivity using Artificial Neural Networks. This study focused more on natural phenomena, such as wind speed, temperature, and sea level, as these environmental factors can affect the productivity level of container ports. As depicted in Figure 2, the Artificial Neural Network (ANN) is composed of a multitude of interconnected components, each representing a neuron. Artificial neural networks (ANNs) are electronic systems that are designed to mimic the neuronal structure of the human brain. While ANNs are a simplified representation of the brain, they aim to replicate the brain's ability to learn and adapt to new and dynamic environments. The objective of an artificial neuron is to emulate the structure and functionality of natural neurons, which comprise inputs (dendrites) and a single output (synapse through axon). The neuron possesses the capacity to ascertain the activation of other neurons.

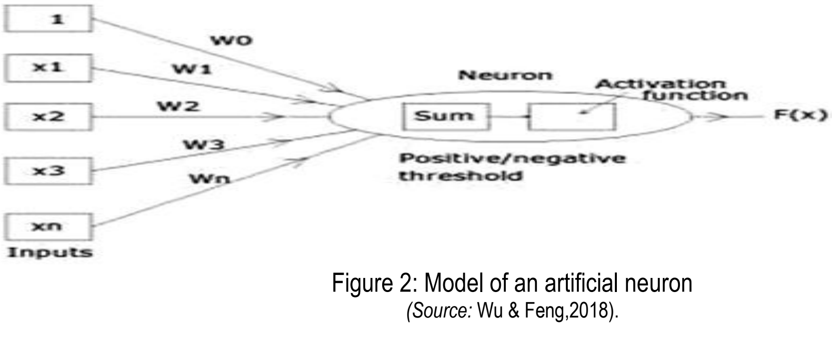

Figure 2: Model of an artificial neuron
(Source: Wu & Feng,2018).

x_1, x_2, x_3, and x_n as the input to the neuron, a bias is added to the neuron along with inputs initialized as 1. W_0, W_1, W_2, W_3, and W_n are the weights as the connection to the signal. Signal strength is found by multiplying the weight by the input. There was one output from a neuron and various inputs from different sources. Activation functions come in many forms, but the sigmoid function is the most common, as given:

$$\boldsymbol{F(x)} = \frac{\mathbf{1}}{\mathbf{1}+\boldsymbol{e}^{-(\sum_{i=1}^{n} x_i w_i)}} \quad (5)$$

Represented by Figure 3 as the sigmoid function.

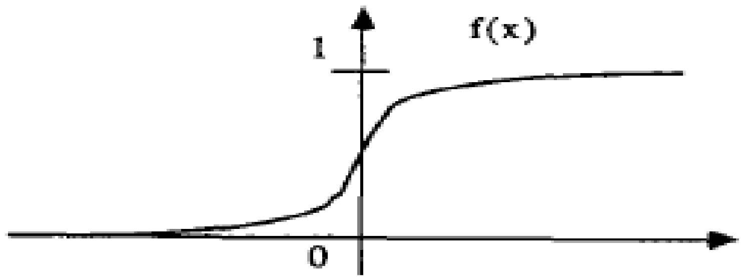

Figure 3: Sigmoid function
(Source: Wu & Feng,2018)

The Multi-Layer Perceptron, or MLP for short, extends the traditional perceptron-based paradigm to a more complex and layered architecture. Alternatively stated, MLP can be characterised as interconnected neural networks comprising neuron layers, wherein the output of a layer is restricted to serving as an input for neurons in the uppermost layer. Moreover, utilizing a non-linear activation function in the neurons of the MLP neural network enables it to capture the significant non-linear characteristics present in the dataset effectively. This property enables the approximation of any continuous function with minimal error by employing sufficiently complex MLPs. The Equation (8) extracted from Jebali & Khraief (2017) can be utilised to assess the i-th neuron in the l-th layer by considering the weight of the link between the i-th neuron in the l-th layer to the j-th neuron in the (l+1)-th layer or the (l+1)-th layer.

$$y_{li} = f_{li}(z_{li}); z_{li} \sum_{j=1}^{n_{l-1}} w(l-1)_j\,, liY(l-1)_j + b_{li} \quad (6)$$

Where y_{li} is the output, f_{li} is the activation function, and b_{li} are the biases, respectively. The amount of neurons in the l^{th} layer is n_1. In addition, $y_{0i} = x_i$. The sum of the weighted outputs from the neurons in the bottom layer turns on the neuron. The training phase of the MLP network aims to minimize an objective function associated with the criteria relevant to the MLP task. The activation of a neuron is determined by the summation of the weighted outputs originating from neurons in the preceding layer. The training technique of the MLP network involves minimizing an objective function that is associated with the criteria relevant to the task performed by the MLP. The equation shown in Equation (9) is a widely applicable formula for binary classification.

$$E(\theta) = \frac{1}{n}\sum_{(x,y)\epsilon D}(y-\hat{y})^2 \quad (7)$$

Assuming that x is a preset input and θ is a training dataset, then D is the collection of weights and biases for the MLP. If the objective function $E(\theta)$ Needs to be slashed. The gradient method can be used. This method says that the amount of an update for the parameter is inversely proportional to the gradient. The speed with which MLP predictions could be made was made possible by a computational approach known as a feedforward algorithm. According to the algorithm, the outputs of the first layer of neurons are used to calculate x, then the outputs of the second layer, and so on, until the outputs of the last layer of neurons are used to determine y (Jebali & Khraief, 2017).

3.0 Results

Table 1 presents the descriptive analysis of the inputs selected for the study, which include the Container Yard Area (m²), Length of Berth (m), and the Number of Cranes. The mean for the selected output, Container Yard Area (m²), is 596,261.7 m². Meanwhile, the mean for the Length of Berth (m) is 2331.8 m and the mean Number of Cranes is 78.3. Regarding the outputs, which are Total Container Throughput (TEUs), the mean value is 28,403,907.1 TEUs, with a median of 4,103,696 TEUs.

Table 2 summarises the results for the first stage of the data analysis. The decision-making units (DMUs) were ranked in descending order based on Total Factor Productivity Changes (TFP) values. It was observed that Port of Tanjung Lepas scored the highest productivity value, equivalent to 0.94. On average, its technological change was 0.935, and no changes in its efficiency value. The next port, in second position, was Port Klang, with a productivity level of 0.910, followed by Penang Port, with a productivity value of 0.854. Miri Port and Bintulu Port scored the last two lowest values of productivity level. The low productivity levels are probably due to the small size of the ports. All ports appeared to experience a productivity level of less than 1, indicating a loss in productivity. The contributing components are due to loss in technological change, as shown across all ports in Table 2.

Table 1: Descriptive Statistics for the Inputs and Output

	Variable	Mean	Median	Std. Deviation	Minimum	Maximum
Input	Container Yard Area (m2)	596261.7	162299	942420.27	48812	2804000
	Length of berth (m)	2331.8	1048.5	2759.4	390	8828
	Number of Cranes	78.3	24.5	124.78	10	374
Output	Total Container Throughput (TEUs)	28403907.1	4103696	49970578.12	386213	141037480

Table 2: Malmquist TFP Indices Using DEA: Model by DMUs

Ranks	DMUs	TFP	TechCh	EffCh
1	Port of Tanjung Lepas	0.940	0.935 (-6.5)	1.000
2	Port Kelang	0.910	0.911(-8.9)	1.000
3	Penang Port	0.854	0.855 (-14.5)	1.000
4	Johor Port	0.852	0.852 (-14.8)	1.000
5	Kuching Port	0.836	0.839 (-16.1)	0.999
6	Kuantan Port	0.827	0.828 (-17.2)	1.000
7	Sabah Port	0.825	0.826 (-17.4)	1.000
8	Rajang Port	0.820	0.821 (-17.9)	1.000
9	Miri Port	0.819	0.82 (-18)	1.000
10	Bintulu Port	0.818	0.819 (-18.1)	1.000

In the second step, under the ANN-MLP, data with predicted output is fed into the network, which is also known as supervised training. SPSS version 26 was used to look at the ANN-MLP. The data was divided into two parts: training and testing. The training sample comprises the data used for training neural networks, enabling the creation of a model. Conversely, the testing sample comprises an independent dataset employed to monitor errors during training, thereby mitigating the risk of overfitting the model. It is strongly suggested that the testing set of data be less than the training set. For this study, the dataset was partitioned so that 70% of the data is used for training and 30% is reserved for testing.

Table 3 presents the model summary of the ANN-MLP, which includes the values for the sum of squared error (SSE) and the relative error for both training and testing. For the training part of the data, which accounts for 70 percent, the SSE value is 13.467, and the relative error value is 0.32. The small value of the relative error, which is close to 0, indicates that the model has a minimal random error component and suggests that the fit is more suitable for prediction. For the testing part, with only 30 percent of the data, the sum of squares is smaller than that of the training partition, at 6.112. The same can be said for the relative error value, which is smaller at 0.266.

Table 3: Model Summary

Training	Sum of Squares Error	13.467
	Relative Error	0.299
Testing	Sum of Squares Error	4.329
	Relative Error	0.304

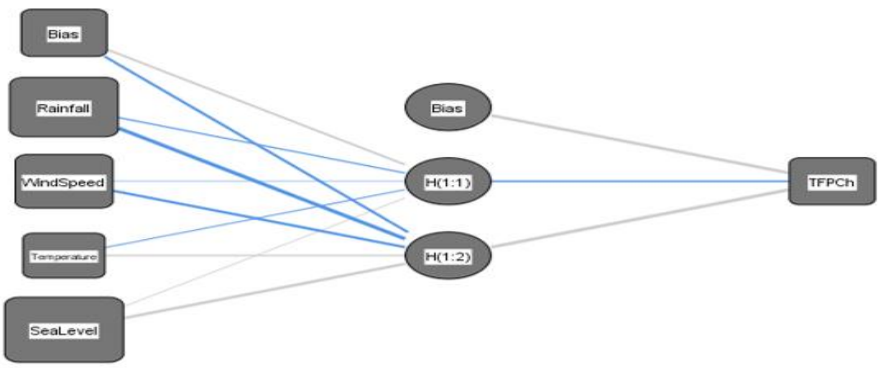

Figure 5: Neural Network Diagram
(Source: Wu & Feng,2018).

The artificial neural network (ANN) used in this study is a conventional feed-forward backpropagation neural network comprising three layers: the input layer, the hidden layer, and the output layer. The neural networks employed in this investigation are depicted in the figure. An MLP neural network is shown in Figure 5. The input layer has four neurons that indicate the things that affect TFPch. The hidden layer consists of one neuron, and the output layer consists of one neuron. The link between the neurons is indicated by the lines connecting them. The colour of the line represents the intensity of the interaction between the neurons, with darker blue lines indicating a stronger relationship between two neurons.

Table 4 displays the data from the neural network architecture shown in Figure 5. The input layer has 5 neurons and 4 contextual parameters, one of which is Bias. The buried layer has 1 neuron. The independent variable in the output layer is Total Factor Productivity (TFP), which has only one unit.

Table 4: Network Information and Model

Input Layer	Environmental Factors	Rainfall, Wind Speed, Temperature, and Mean Sea Level
	Number of units	4
Hidden Layer	Number of units	1
Output Layer	Independent Variable	Total Factor Productivity
	Number of units	1

Changes in the network's model-predicted value for different environmental factors are used to determine the importance of these factors in affecting Total Factor Productivity (TFP). Table 5 shows the percentage of normalized importance of the environmental factor. It can be shown that the mean sea level has the highest percentage (100 percent), followed by the rainfall (77.2 percent), wind speed (39.7 percent), and lastly is temperature (18.6 percent).

Table 5: Independent Variables Importance

	Importance	Normalized Importance
Rainfall	0.328	77.2%
Wind Speed	0.168	39.7%
Temperature	0.079	18.6%
Mean Sea Level	0.425	100.0%

Figure 6 presents the importance bar chart, sorted in descending value, where the mean sea level is listed first with the highest value of 0.425 and then, followed by rainfall with a value of 0.328 and windspeed with a value of 0.168. Temperature is in last place with a value of only 0.079.

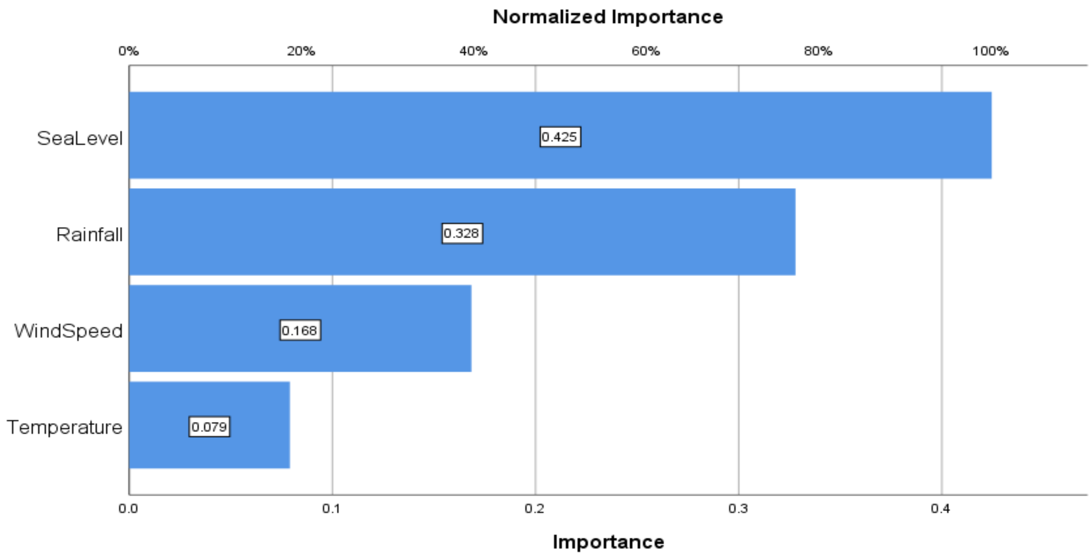

Figure 6: Graph for the Normalized Importance

Overall, the results indicate that the mean sea level and rainfall are the most significant factors affecting the TFP scores, as their percentage of normalized importance is closer to 100 percent. The findings presented here align with those of Jebbab and Sierra (2022), who observed that even a marginal increase in sea level and storm surge height could substantially impact the operations of container terminals and potentially inundate the docks. Transient or persistent flooding may result from the direct consequences of sea level rise exceeding the elevation of the docks. Such flooding may impede or disrupt operations.

4.0 Conclusion

The goal of this study is to investigate the key environmental elements influencing container port productivity in Malaysia. The investigation was conducted in two stages, with the first employing MPI and the second utilizing ANN-MLP. The results of the first stage revealed that the Port of Tanjung Pelepas appears to be the first and has the highest production level. Port Klang ranked second, followed by Port Penang. These three ports are the largest and most important in Malaysia and are among the 13th busiest ports globally.

The second stage revealed that sea level is the most important factor influencing Total Factor Productivity (TFP) ratings. Rainfall is the second most important component. Sea level and rainfall are the major environmental elements affecting Malaysian ports. These findings were consistent with Sherman (2019), who found that weather occurrences affected various port activities. For example, storms and rain significantly impact cargo lashing during loading/unloading, movement, and storage within the terminal. At the same time, wind has the most significant impact on crane performance and berthing. The outcomes of this study should provide port authorities with more information about the productivity level of their container ports. This can assist the port authority's management staff in taking action and improving their respective container ports. The port authorities should also be able to carefully plan their ship routes to prevent environmental factors from impairing the production level of their container port.

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Paper Contribution to Related Field of Study

This paper has contributed to benchmarking the productivity of Malaysian ports and identified the sources of their performance. Apart from that, this study identifies environmental factors that significantly affect the productivity values of Malaysian ports.

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