

A Multi-Method Assessment for Modeling the Ecological Footprint Response to Air Freight Volume, Export Performance, and Natural Resource Rents

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Abstract

The rapid expansion of global supply chains, fueled by air freight logistics, export-driven development, and resource extraction, poses significant environmental challenges. This situation requires an urgent assessment of its impact on our ecological footprint. This paper examines the effects of air freight volume, export performance, and natural resource rents on Malaysia's ecological footprint using time series data from 1980 to 2021. To identify the most influential factors, the study employs the Gray relational analysis similarity based ranking technique. Additionally, the study employs the Auto regressive Distributed Lag (ARDL) model to evaluate both the long-term and short-term impacts of these variables on environmental degradation. This study provides significant insights and highlights limitations and suggests future research directions. This framework will assist practitioners, stakeholders, and policymakers in making informed decisions and establishing a sustainable growth network.

Keywords

Ecological footprint, Air freight, Resource extraction, ARDL, GRA, Ranking, Environmental sustainability.

1. Introduction

Factors contributing to environmental degradation, such as economic expansion, energy consumption patterns, technological advancements, and various social and industry-related variables, have been thoroughly examined in existing literature. Rapid global market expansion, driven by export-import activities, logistics intensity, and resource extraction, plays a significant role in shaping biological production patterns. Therefore, this study emphasizes the need to quantify air freight volume, export performance, and natural resource rents in relation to their ecological footprint. It reveals the consumption patterns among these variables and highlights the necessity for optimized resource allocation.

This study employs Gray Relational Analysis (GRA) to rank the influencing variables and illustrate their relationships with the ecological footprint. Additionally, it utilizes the Auto regressive Distributed Lag (ARDL) model to evaluate both long-run and short-run impacts of the variables on the environment. Granger causality analysis is also applied to

explore the bidirectional relationships among the variables. This hybrid framework aims to provide a solid foundation for policymakers and practitioners to assess sustainable growth, economic expansion, and efficient resource utilization within active export-import frameworks.

1.1 Objectives

- To analyze the long-run and short-run impacts of air freight volume (ATF), export performance (EVI), and total natural resource rents (TNRR) on ecological footprint (EF) using the ARDL model.
- To utilize Gray Relational Analysis to optimize the interactions of logistic intensity, export supply chain, and resource utilization, and properly rank them.
- To develop a novel hybrid framework that connects optimization techniques with econometric analysis, while also exploring machine learning and deep learning methodologies alongside optimization methods.

2. Literature Review

The growing strain on global ecosystems from rapid industrialization necessitates thorough research into environmental degradation. Recent studies leverage the Ecological Footprint (EF) as a key indicator, analyzing its ties to energy consumption, economic growth, and resource use using methods like the Autoregressive Distributed Lag (ARDL) model and Grey Relational Analysis (GRA).

A central theme explores the energy-growth-environment nexus, often through the Environmental Kuznets Curve (EKC) hypothesis. Research by Li et al., 2023 on G20 nations indicates that while non-renewable energy worsens ecological footprints, renewable energy can mitigate these effects. Wu et al., 2025 find a long-term balance between clean energy adoption and ecological stress in China. However, Pata et al., 2023 note that emerging economies like Turkey struggle to reach the EKC turning point, influenced by demographic factors. In developed nations like Finland, Georgescu & Kinnunen, 2024 reveal that energy consumption patterns still drive environmental degradation despite the introduction of greener technologies through foreign direct investment (FDI).

Recent work emphasizes the importance of structural transformation and institutional quality. Doytch et al., 2025 show that Information and Communication Technology (ICT) can reduce environmental impacts by decoupling growth from resource intensity, while Hardi et al., 2024 warn that unregulated economic activities can exacerbate ecological footprints. Urbanization's impact varies; Rehman & Rehman, 2022 identify it as a significant emissions driver in Asia, while Amer et al., 2022 find urbanization can lower ecological footprints in Gulf Cooperation Council (GCC) countries due to infrastructure efficiencies. The fiscal policy reform in Colombia led to municipalities' investment decisions becoming less reliant on resource revenue, particularly for producer municipalities (Collazos-Ortiz & Wong, 2024).

The debate over natural resource rents is complex. While Imran et al., 2025 link fossil fuel reliance to degradation, Amer et al., 2022 note that resource wealth can promote sustainability if managed well. Ganhane & Stage, 2024 emphasize that underestimating extraction costs leads to inadequate policies. Additionally, Study by Sohag et al., 2024, shows that strong environmental policies can mitigate resource dependence issues. According to Nathaniel et al., 2025, a 1% increase in natural resources leads to a 0.064% increase in the ecological footprint (EF) in Sub-Saharan Africa (SSA). Besides, a negative direct effect was observed for renewable energy consumption and total resource rent on ecological footprint (EFP), while urbanization, growth, and industrialization had positive direct effects (Ragmoun, 2023).

Methodologically, the field is moving toward hybrid approaches to address data uncertainty and causal complexity. H. Wu et al., 2025 propose a weighted GRA model to improve the identification of carbon drivers. Besides, the study by Adabor, 2023 confirms that financial development indicators such as net domestic credit and monetary sector credit to the private sector are crucial for increasing natural gas resource extraction by using ARDL model. The continued use of ARDL and its variants underlines the need for understanding both short-term dynamics and long-term equilibria in environmental economics. This study aims to integrate GRA and ARDL frameworks to analyze how air freight, export performance, and resource rents collectively shape the ecological landscape.

3. Methodology

3.1 Data Description

The data sample for Malaysia covers the time period from 1980 to 2021 and has been collected from the World Development Indicators (WDI) database. The dependent variable in the model is Ecological Footprint (in global hectares per capita). The independent variables are: Export performance – denoted as export value index (2015=100), Air transport freight (Million ton-km), Total natural resource rent (%of GDP). All variables were log transformed to stabilize variance and ease interpretation. The log-transform normalizes the data gives and hence the interpretationally figure out afterwards. Table 1 describes the data description in the below.

Table 1. Description of the variables

Variables	Description	Logarithmic form	Unit
EF	Ecological footprint	LEF	Global hectares
EVI	Export value index	LEVI	2015=100
ATF	Air transport freight	LATF	Million ton-km
TNRR	Total natural resource rent	LTNRR	%of GDP

3.2 Grey Relational Analysis (GRA)

Grey Relational Analysis (GRA) is used on this dataset to determine the optimum condition of EVI, ATF, TNRR to obtain the best quality characteristics of EF. This involves 4 steps, which are, Data preprocessing & normalization, Absolute difference, Grey relational coefficient, and Grey relational grade. After normalizing the dataset, the absolute difference between the reference and each comparison sequence is calculated. The grey relational coefficient (GRC) is then derived, followed by the grey relational grade (GRG), which ranks the alternatives.

Normalization:

$$x'_i(k) = \frac{x_i(k) - \min x_i(k)}{\max x_i(k) - \min x_i(k)}$$

Absolute difference:

$$\Delta_i(k) = |x'_0(k) - x'_i(k)|$$

Grey relational coefficient:

$$\xi_{i(k)} = \frac{\{\Delta_{\{\min\}} + \zeta, \Delta_{\{\max\}}\}}{\{\Delta_{i(k)} + \zeta, \Delta_{\{\max\}}\}}$$

where, the distinctive coefficient is represented by ξ and assume to be $\xi = 0.5$ as a distinctive coefficient.

Grey relational grade:

$$\gamma_i = \left\{ \frac{1}{n} \right\} \sum_{k=1}^n \xi_{i(k)}$$

Grey Relational Analysis (GRA) is applied in three different forms: Deng's GRA, Absolute GRA, and Secondary Synthetic GRA. Deng's GRA evaluates the relative similarity between a reference sequence and comparison sequences through data normalization, deviation calculation, the grey relational coefficient $\xi_i(k) = \frac{\Delta_{\min} + \zeta \Delta_{\max}}{\Delta_{i(k)} + \zeta \Delta_{\max}}$, and the grey relational grade $\gamma_i = \frac{1}{n} \sum \xi_i(k)$.

3.3 Absolute degree grey incidence analysis (ADGIA)

Absolute GRA measures the absolute proximity of raw data without normalization using $d_i(k) = |x_0(k) - x_i(k)|$ and $\xi_i^{abs}(k) = 1 - \frac{d_i(k)}{\max d_i(k)}$. The absolute GRA model introduced the concept of the absolute degree of grey relation that is also known as the ADGIA

model. Let the system behavior data sequence represent as $X_i = (x_i(1), x_i(2), \dots, x_i(n))$ and C indicates the satisfying sequence operator, and $X_i(L)c = (x_i(L)c - x_i(1); L = 1, 2, 3, \dots, n)$ then C is point operator starting from zero and X_iC is known as X_i 's zero scale point image It is written as follows: $X_tC = (\chi_t(L)c - \chi_t(1); L = 1, 2, 3, \dots, n)$

$$(i) \quad X_iC = X_i^0 = (x_i^0(1), x_i^0(2), \dots, x_i^0(n))$$

$$(ii) \quad |s_i| = \left| \sum_{L=2}^{n-1} x_i^0(L) + \frac{1}{2} x_i^0(n) \right| \text{ and } |s_j| = \left| \sum_{L=2}^{n-1} x_j^0(L) + \frac{1}{2} x_j^0(n) \right|$$

The absolute difference between $|s_i - s_j| = \left| \sum_{L=2}^{n-1} (x_i^0(L) - x_j^0(L)) + \frac{1}{2}(x_i^0(n) - x_j^0(n)) \right|$ then the absolute degree of grey relation (ADGIA model) is computed as $\varepsilon_{01} = \frac{1+|s_0|+|s_1|}{1+|s_0|+|s_1|+|s_0-s_1|}$

3.4 Second synthetic degree of grey incidence analysis (SSDGIA) model

To enhance robustness, Secondary Synthetic GRA integrates both methods by combining their grades through $\gamma_i^{SS} = \lambda\gamma_i + (1 - \lambda)\gamma_i^{abs}$, producing a comprehensive performance indicator. This three-level framework ensures reliable variable ranking under different data characteristics.

3.5 Model Specification

This analysis explores the relationship between the Ecological Footprint of Malaysia and factors like Export performance, Air transport freight, and the Total natural resource rent between the years 1980 and 2021. It employs time series analysis to identify historical trends within the dataset. Annual trend analysis is used to reduce seasonal variations and smooth out data inconsistencies, while recognizing that structural breaks must be addressed through formal break tests. Figure 1 represents the methodological summary and flow of the study.

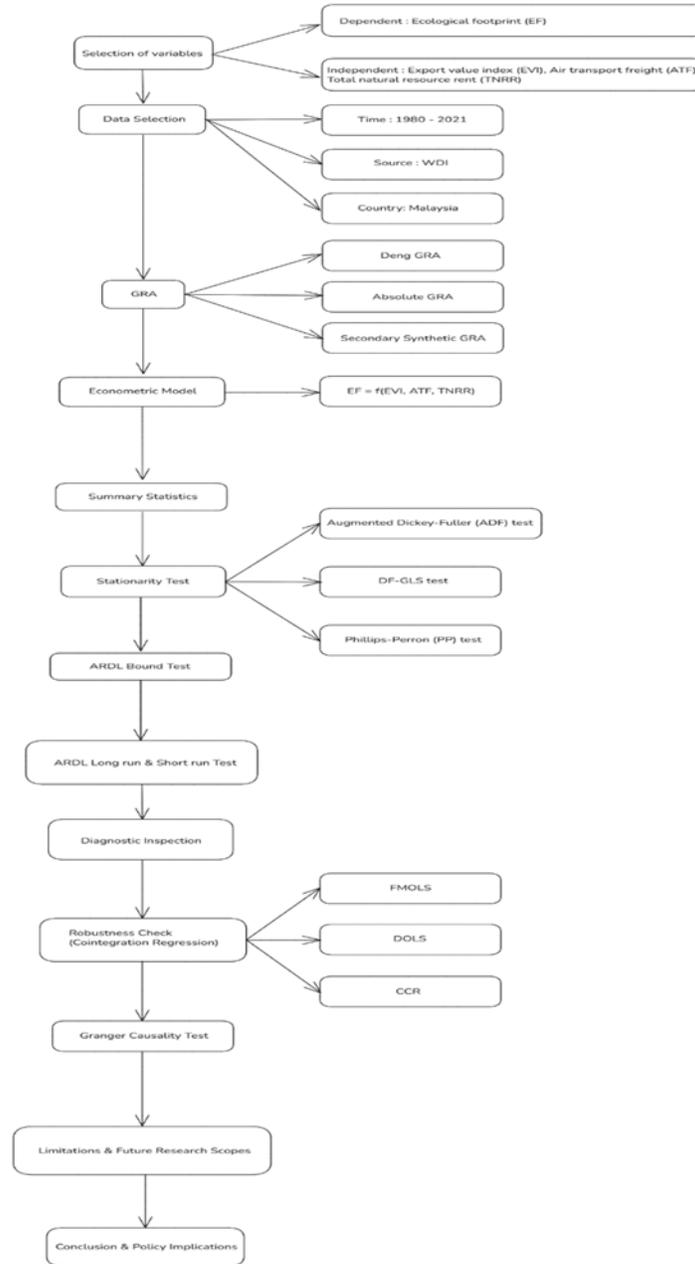


Figure 1. Process Flow Diagram of the Analysis

The relationship at time, t may be explained through the following theoretical expression:

$$EF_t = f(EVI_t, ATF_t, TNRR_t)$$

The model illustrates the relationship between Ecological Footprint and the important factors that influence it. This theoretical framework will be tested using the following linear econometric model:

$$EF_t = \tau_0 + \tau_1EVI_t + \tau_2ATF_t + \tau_3TNRR_t + \varepsilon_t \quad (1)$$

Where, τ_0 = Intercept term; τ_1, τ_2, τ_3 = Coefficients for the respective independent variables and ε_t is the Error term at time t

The ARDL model is efficient for small sample sizes and time series annual environmental data. The model can handle regressors with different lag lengths, selected using information criteria such as AIC or BIC. Before implementing the

error correction representation, a bounds cointegration test is conducted to verify the existence of a stable long run relationship.

Equation (1) can be represented in logarithmic form as,

$$LEFT_t = \tau_0 + \tau_1 LEVI_t + \tau_2 LATF_t + \tau_3 LTNRR_t + \varepsilon_t \quad (2)$$

3.6 Stationarity Check

A stationary time series in data analysis consists of a constant mean and variance in the series, which are a must for reliable results and prevent spurious outcomes. Stationarity ensures F-test results stay valid when the series is integrated of order I(0) or I(1). If the series is I(2), the ARDL approach is invalid because the asymptotic critical values used in the bounds test assume that the variables are at most I(0) and I(1). Non-stationary series may lead to permanent shocks and model misspecification outcomes because of trends or structural breaks.

3.7 ARDL Bound Test

The ARDL bounds test assesses long-run relationships by expressing the model in its unrestricted error-correction form. The test provides two critical bounds: the lower bound assumes all variables are I(0), and the upper bound assumes they are I(1). If the statistic falls between the bounds, the result is inconclusive. The test is valid only when no variable is I(2). Equation (3) presents the long-run cointegration relationship.

$$\Delta LEFT_t = \alpha_0 + \alpha_1 LEFT_{t-1} + \alpha_2 LEVI_{t-1} + \alpha_3 LATF_{t-1} + \alpha_4 LTNRR_{t-1} + \sum_{i=1}^K \gamma_1 \Delta LEFT_{t-i} + \sum_{i=1}^K \gamma_2 \Delta LEVI_{t-i} + \sum_{i=1}^K \gamma_3 \Delta LATF_{t-i} + \sum_{i=1}^K \gamma_4 \Delta LTNRR_{t-i} + \varepsilon_t \quad (3)$$

The ARDL model incorporates lagged dependent and independent variables to capture both long-run equilibrium relationships and short-run adjustment dynamics within a single framework. Lag lengths were selected using the Akaike Information Criterion. After confirming cointegration through the ARDL bounds test, the long-run relationship was estimated using equation (3), and short-run coefficients were obtained from equation (4) to assess long-term effects.

$$\Delta LEFT_t = \alpha_0 + \alpha_1 LEFT_{t-1} + \alpha_2 LEVI_{t-1} + \alpha_3 LATF_{t-1} + \alpha_4 LTNRR_{t-1} + \sum_{i=1}^K \gamma_1 \Delta LEFT_{t-i} + \sum_{i=1}^K \gamma_2 \Delta LEVI_{t-i} + \sum_{i=1}^K \gamma_3 \Delta LATF_{t-i} + \sum_{i=1}^K \gamma_4 \Delta LTNRR_{t-i} + \theta ECM_{t-1} + \varepsilon_t \quad (4)$$

4. Result & discussion

This section illustrates the results of the Gray Relational Analysis (GRA) method. Table 2 displays the ranking of variables, including air transport, freight, export value index, and total natural resource rents, in relation to the dependent variable, the ecological footprint, based on the raw data. The GRA method utilizes three models: DENG GRG, Absolute GRG, and Second Synthetic GRG. Each model addresses different aspects, such as baseline sensitivity to pattern similarity among variables, magnitude-based proximity, and the stabilization of rankings under noisy data, respectively.

Table 3 presents the ranking criteria that have the most significant impact on the ecological footprint, based on their DENG GRG, Absolute GRG, and Second Synthetic GRG values. Air transport and freight consistently rank first across all three models, with DENG GRG, Absolute GRG, and Second Synthetic GRG. Total natural resources rank as the second most influential factor, with a DENG GRG value of 0.5519 and a Second Synthetic GRG value of 0.52599, while it ranks third in the Absolute GRG. The export value index holds the third rank in DENG GRG at 0.5144 and SSGRG at 0.50721. Figure 2 clearly depicts the rankings of the GRG values across the different types of GRA methods.

Table 2. Evaluation of ecological footprint through Grey models

Variables	Deng GRG	Rank	Second Synthetic GRG	Rank
Air transport, freight	0.81175616	1st	0.6558	1st
Export value index	0.51442365	3rd	0.50721	3rd
Total natural resources rents	0.55198283	2nd	0.52599	2nd

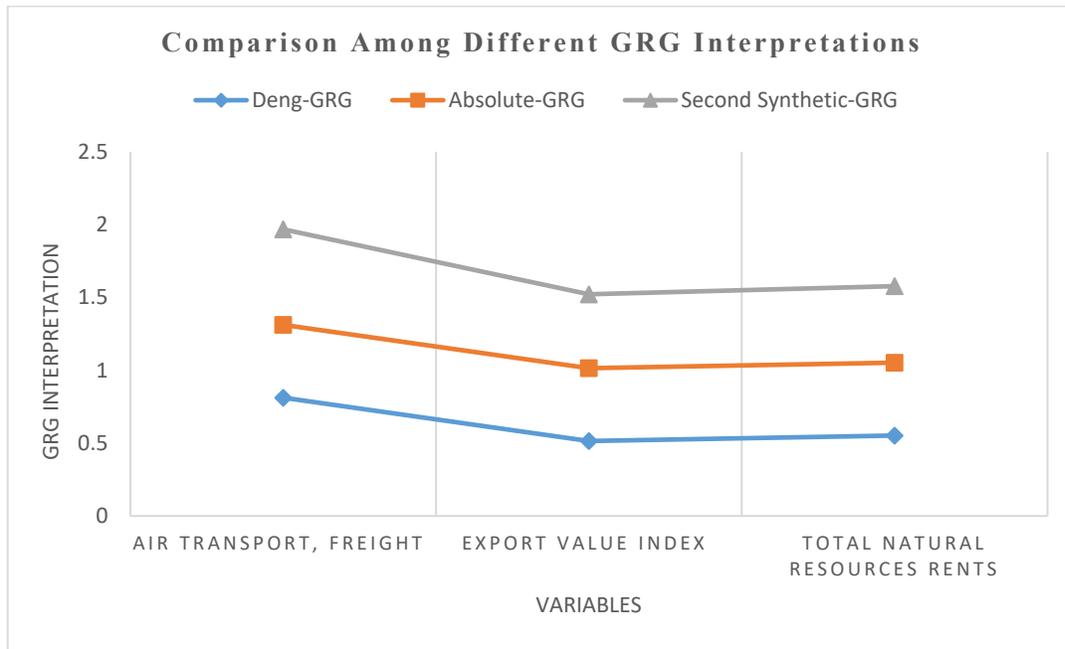


Figure 2. Graphical representation illustrating GRG's interpretation of air transport freight, the export value index, and the overall natural resource rents in relation to ecological footprints.

Table 3. Grey relational model wise ranking criteria contributing in Ecological Footprint

Grey Relational Models	Ranking Descriptions
Deng GRG	Air transport, freight > Total natural resources rent > Export value index
Absolute GRG	Air transport, freight > Export value index > Total natural resources rent
Second Synthetic GRG	Air transport, freight > Total natural resources rent > Export value index

This section demonstrates the outcomes of the ARDL model thoroughly, including several tests like descriptive statistics, unit root test, F-bound test, ARDL long-run test, error correction model, diagnostic inspection, cointegration tests, and Granger causality test.

Table 4 represents the descriptive statistics of the variables where ecological footprint (LEF) demonstrates relatively stable characteristics with a mean value of 18.19 and a median of 18.30, indicating a symmetric distribution. The export value index (LEVI) shows considerable variation, ranging from 1.7726 to 5.0086, reflecting Malaysia's evolving export performance over three decades. The normality tests confirm that all variables follow normal

distributions. Skewness values remain close to zero for all variables, with the LEF showing slight negative skewness (-0.5441) and other variables displaying similar patterns. Kurtosis values below 3 indicate platykurtic distributions, suggesting flatter tails compared to the normal distribution.

Table 4. Descriptive Statistics

Variables	LEF	LEVI	LATF	LTNRR
Mean	18.19289	3.629625	6.867302	2.585404
Median	18.30572	3.817559	7.227787	2.533551
Maximum	18.73582	5.008633	7.956219	3.631865
Minimum	17.38184	1.772633	4.699571	1.513272
Std. Dev.	0.451669	1.05942	0.97174	0.539317
Skewness	-0.544175	-0.495206	-0.875352	0.094211
Kurtosis	1.856702	1.824058	2.514584	2.135901
Jarque-Bera	4.360362	4.136571	5.776041	1.368796

Table 5 represents the stationarity analysis by employing three robust unit root tests to examine the integration properties of the variables. The ADF test reveals that most variables are non-stationary at levels but achieve stationarity after first differencing. The ecological footprint shows stationarity at the 1% significance level (-4.0208) and becomes stationary after the first differencing. Besides, the export value index, air transport freight and total natural resources rent variables also require first differencing to achieve stationarity, respectively, (-4.908), (-8.4077) and (-5.2720) at 1% significance level. The consistency is supported by the PP test, being strongly stationary at first differencing. Breakpoint unit root test shows stationarity at first difference alongside the break year mentioned. The test shows stationarity for all of the variables.

Table 5. Result of Unit Root Test

	ADF		PP		Zivot-Andrew test	
Variables	Level	Level	1 st difference	1 st difference	t-statistic	Break year
LEF	-3.59	-3.47	-21.19***	-4.02***	-8.95***	2009
LEVI	-2.49	-2.46	-4.97***	-4.49***	-5.59***	1995
LATF	-0.25	-0.92	-10.77***	-8.40***	-6.99**	2008
LTNRR	-2.94	-2.86	-5.45***	-5.27***	-6.11**	2000

***p<0.01

Table 6 presents the ARDL F-bound test statistics, which indicate a test value of 5.4011. This value exceeds the critical upper boundary of the significance range, leading to the rejection of the null hypothesis of no long-run relationships. Consequently, it confirms a long-run relationship among LEF, LATF, LEVI, and LTNRR.

Lag length selection

The Akaike information criteria is used to pick the lag length of the ARDL model in this study, which examines the top 20 model models. The model's critical lag length as recommended by ARDL (4,4,2,1), shown in the Figure 3.

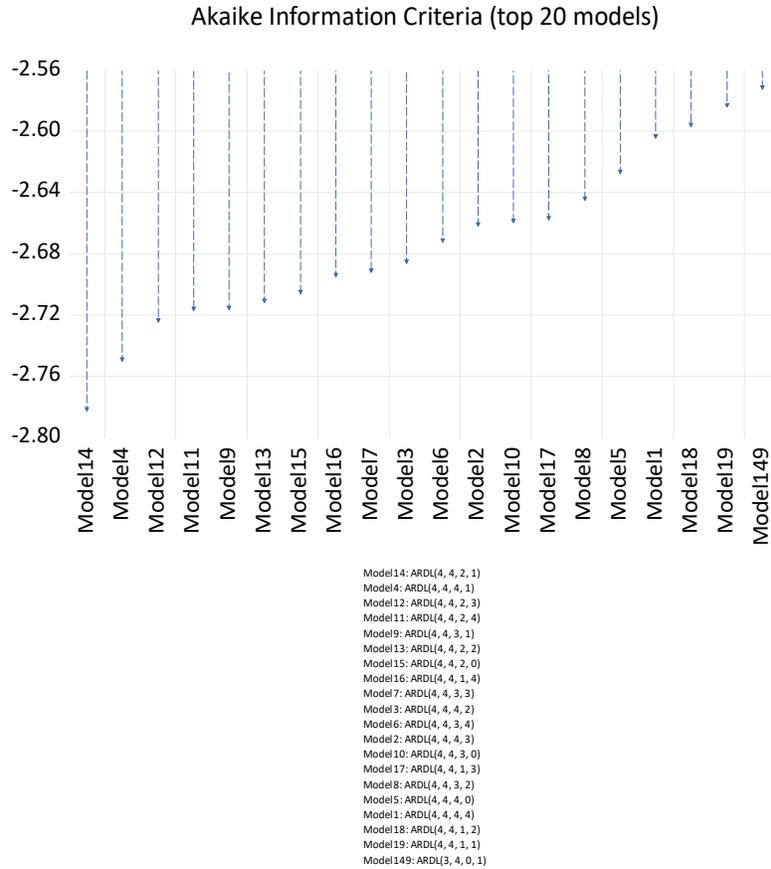


Figure 3. Akaike information Criterion Lag length selection

Table 6. Result of the ARDL bound test

Test	Value	Significance	I(0)	I(1)
F-statistic	5.401122	10%	2.37	3.2
k	3	5%	2.79	3.67
		2.50%	3.15	4.08
		1%	3.65	4.66

Table 7 demonstrates the ARDL long-run and short-run outcomes. In both the long run and short run, the variables show a consistent sign convention like LEVI, which worsens the ecological footprint by 0.219% with a very high significance level (p value=0.0002). Whereas in the short run, it also intensifies the environmental pressure by an increased effect of 0.569% with a very good significance level (p value=0.0000), indicating weak trade management, infrastructure, and lower technological advancement in the export supply chain, aligning with the existing literature's support. As well as, LTNR also shows sign consistency as 0.186% (p value=0.0008) in the long run and 0.1087% in the short run that helps to cut the ecological pressure by supplying resource extraction supply, forestry value-added, etc., with relevance to the existing literature on the other models too. LATF intensifies the LEF by 0.107% (p value=0.0031) in the long run and reduces the ecological tension by 0.157% in the short run, indicating a greener, sustainable, and technology-based air logistics inspection and infrastructures.

Table 7. ARDL long- and short-run analysis

Variables	Long Run		Short Run	
	Coefficient	t-statistics	Coefficient	t-statistics
LEVI	0.219521***	4.434725	0.569761***	8.518694
LATF	0.107347***	3.300507	-0.157614***	-2.820406
LTNRR	-0.186297***	-3.835814	-0.108759	-1.575491
C	17.12367***	98.66238	-	-
ECM (-1)			-1.203929***	-5.630474
R ²	0.965351			
Adjusted R ²	0.934369			

***p<0.01

The linear ARDL model is represented in the equation 5

$$EC = LEF - (0.2915 * LEVI + 0.1073 * LATF - 0.1863 * LTNRR + 17.1237) \quad (5)$$

Table 8 represents the diagnostic inspection of the ARDL model. Jarque-Bera test holds a significant p-value of 0.7404, which is much greater than the threshold value of 0.1. This indicates the normal distribution of the residuals in the model. Breusch-Godfrey correlation LM test has a p-value of 0.955, indicating the acceptance of the null hypothesis that there is no serial correlation among the residuals. Breusch-Pagan-Godfrey test confirms the stable variance among the regressors with a p-value of 0.556, accepting the null hypothesis of homoskedasticity. Ramsey-RESET confirms the model's inconsistency and checks if there's any omitted variables presence. Here, the p-value of the F-statistics is 0.420, indicating that the model is properly specified and consistent and there is no omitted variables in the model.

Table 8. Diagnostic Inspection

Diagnostic Investigation	Coefficient	p-value	Decision
Jarque-Bera test	0.600919	0.7404	Residuals are normally distributed
Breusch-Godfrey LM test	0.045599	0.9555	No serial correlation exists
Breusch-Pagan-Godfrey test	0.915348	0.5565	No heteroscedasticity exists
Ramsey RESET test	0.821827	0.4235	The model is properly specified

To confirm the robustness of the findings, the study further conducts the CUSUM and CUSUMSQ tests for diagnostic inspections. Figure 4 illustrates the results of these tests within critical boundary lines. The plot highlights a 5% threshold boundary, which demonstrates the stability of the model's parameters over the observed time period and reinforces the robustness of the model's outcomes. Table 9 presents the results of the co-integration tests conducted using the FMOLS, DOLS, and CCR methods. The empirical findings indicate a consistent sign convention in both the long and short-run coefficients obtained from the ARDL approach. The R² values for the FMOLS, DOLS, and CCR tests are 0.979, 0.981, and 0.978, respectively, indicating a very good fit for the model. Additionally, the adjusted R² values are also high, at 0.977, 0.972, and 0.977, further supporting the model's robustness and the extent to which it is rigorously explained. Table 10 illustrates the pairwise granger causality of among the variables towards LEF and checks the bidirectional causal relationship.

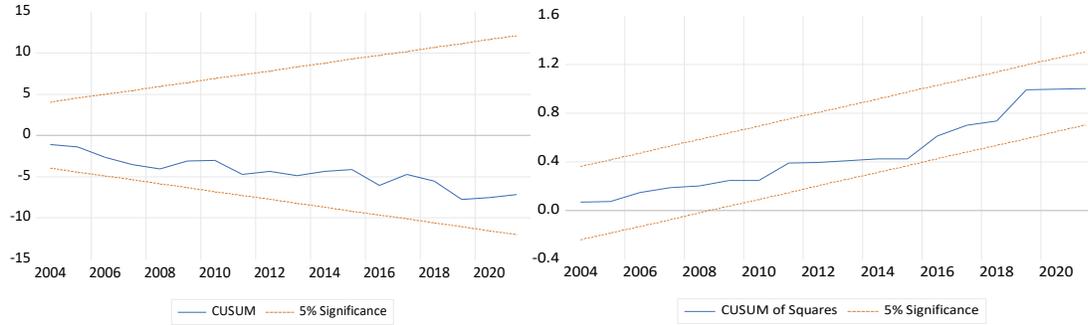


Figure 4. CUSUM & CUSUMSQ graph

Table 9. Result of FMOLS, DOLS and CCR test

Variables	FMOLS		DOLS		CCR	
	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
LEVI	0.336874***	7.486049	0.348986***	4.221479	0.332151***	6.775868
LATF	0.044417	1.428815	0.040704	0.79289	0.046414	1.442832
LTNRR	-0.100811	-1.730394	-0.079971	-0.777758	-0.106073	-1.687717
C	16.92423	76.06705	16.85953	46.14579	16.94092	70.23921
R^2	0.979087		0.981158		0.978982	
Adjusted	0.977391		0.972462		0.977278	

***p<0.01

Table 10. Pairwise Granger Causality Test

Causality Direction	F-statistics	p-value	Decision
LATF → LEF	0.10623	0.8996	⊗
LEF → LATF	1.48573	0.2456	⊗
LEVI → LEF	4.23024***	0.0262	✓
LEF → LEVI	1.52839	0.2365	⊗
LTNRR → LEF	0.92995	0.4078	⊗
LEF → LTNRR	2.6677	0.0891	⊗

5. Limitations and Future research scope

The primary constraint accounted in this study is the limited time frame and the unavailability of data. Quarterly or monthly data can provide more insights to explore the pattern of the data broadly. This analysis examines the interconnections between the environment, export, and natural resources utilization in Malaysia. Future research could delve into a broader range of variables, including institutional quality, patent applications, broad money supply, inflation, governance effectiveness, social and political parameters, green finance, health expenditure, vehicle regulations, and to other countries. Panel ARDL can facilitate comparisons of regional data, while dynamic ARDL (DYN-ARDL) can handle the complexities of data series dynamics. To enhance model performance, advanced econometric methods like nonlinear ARDL (NARDL) and machine learning techniques (XGBOOST, RNNs, ANN and LSTM) could be employed. These methods can strengthen the findings and advance the existing literature. Moreover, other optimization techniques like response surface methodology (RSM), Bayesian optimization to deliver a more robust insights to rank across the variables.

6. Conclusion

This paper illustrates the causal relationship among air transport freight, export value index, and total natural resources to the ecological footprint of Malaysia. This study employs ARDL model and gray relation analysis to analyze the long run and short run relationship between the variables and rank them based on their data pattern, respectively. Empirical study shows that air transport freight intensifies the ecological footprint in all GRG models, whereas total natural resources stand second on both Deng GRG and SSRG model. Export value index has a variance in the ranking to affect the environmental stress such as it has a lesser effect on both Deng GRG and SSRG as third rank but shows a slight variance in the ranking in the Absolute GRG. ARDL analysis shows that export value index intensifies the ecological footprint by 0.219% in the long run and reduces it by 0.569% in the short run with a high significant level. Here, total natural resources also show a constant negative relationship in both the long and short run, 0.186% & 0.108%, respectively. But air transport freight increases the ecological footprint by 0.107% and by the time being on the short run it reduces by 0.157%, indicating an optimized logistic operation management, technology, and infrastructure advancement. This paper uses a novel framework by integrating gray relation analysis optimization tool to ARDL methodology that will add a new dimension in the environmental and econometrics analysis. It will help the practitioners, stakeholders, and policymakers to look over which factor affects the most and can make a sustainable and resource-allocated economy.

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