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Ekonomikalia
Journal of Economics

Vol. 3, No. 1, 2025

Do Natural Disasters, Fossil Fuels, and Renewable Energy Affect CO_2 Emissions and the Ecological Footprint?

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Article History

Received 6 February 2025
Revised 8 April 2025
Accepted 17 April 2025
Available Online 27 April 2025

Keywords:
Environmental quality
CO_2 emissions
Ecological footprint
Natural disasters
Fossil fuels
Renewable energy
Indonesia

Abstract

Climate change is a global concern driven by increasing pollution through rising CO_2 emissions and growing ecological footprint from human activities. This research investigates how environmental quality (proxied by CO_2 emissions and ecological footprint) in Indonesia is affected by multiple factors, including natural disasters, fossil fuels, renewable energy consumption, economic growth, and capital formation from 1965 to 2022. The analysis employs the Autoregressive Distributed Lag (ARDL) model, with robustness ensured using Dynamic Ordinary Least Squares (DOLS), followed by Granger causality tests to examine dynamic relationships between variables. The findings show that natural disasters, fossil fuel consumption, and economic growth contribute to increasing CO_2 emissions in the long run, while renewable energy consumption helps reduce them. Natural disasters exhibit a negative but insignificant impact on the ecological footprint. Economic growth increases the ecological footprint, whereas capital formation helps reduce it in the long run. In the short run, fossil fuels are found to increase CO_2 emissions, while renewable energy reduces them. Natural disasters are found to increase the ecological footprint. Additionally, the Granger causality test confirms a unidirectional relationship from both natural disasters and economic growth to environmental quality. This study recommends that Indonesia implement integrated strategies focused on accelerating green energy adoption and enhancing disaster resilience to achieve environmental quality.

1. Introduction

Climate change has emerged as an increasingly pressing global concern, fueled by the ongoing increase in greenhouse gas emissions and the growing ecological footprints of various nations [1–3]. The heating of the Earth's atmosphere has exacerbated environmental deterioration, sparked extreme weather phenomena, and imposed further strain on ecosystems and human communities [4, 5]. In particular, CO_2 emissions have soared to unprecedented levels, playing a significant role in global warming and climate volatility [6–8]. Additionally, the ecological footprint, which serves as a comprehensive measure of environmental strain, reflects the degree of human demand on natural resources, encompassing land utilization, energy use, and waste production [9–11]. As environmental issues intensify, particularly in swiftly developing nations, it is crucial to comprehend the fundamental factors that contribute to these escalating environmental pressures [11, 12]. One of the countries experiencing rapid economic growth alongside rising CO_2 emissions and an expanding ecological footprint is Indonesia.

According to Our World in Data [13], as presented in Figure 1, from 1965 to 2022, Indonesia experienced a striking upward trend in both CO_2 emissions and its ecological footprint, reflecting rapid industrialization, urbanization, and sustained economic growth. In 1965, CO_2 emissions were approximately 24.7 million tons, but by 2022, they had surged to over 737 million tons, representing an almost 30-fold increase [13]. Similarly, the country's ecological footprint more than tripled, rising from around 129 million global hectares to over 462 million [14]. This parallel growth highlights a strong correlation between emissions and broader environmental impact. Sharp increases, particularly from the late 1990s onward, suggest intensified energy use, deforestation, and industrial expansion. Importantly, even during periods when CO_2 emissions slightly declined, such as during the 1998 financial crisis and the 2020 pandemic, the ecological footprint remained elevated. This indicates that environmental degradation is driven not only by emissions but also by land use, resource consumption, and demographic pressures [15, 16].

Indonesia, as one of the fastest-growing economies in Southeast Asia, faces mounting environmental challenges driven by a range of interconnected factors. Environmental degradation in the country is influenced by natural disasters, fossil fuel dependence, renewable energy adoption, economic growth, and capital formation [17–19]. While natural disasters are frequently viewed as consequences of climate change, they can also serve as catalysts for emissions and ecological strain due to the reconstruction efforts and heightened energy consumption that follow [17, 20, 21]. Fossil fuels remain the dominant source of energy worldwide, and their combustion is a major source of CO_2 emissions and the depletion of natural resources, further exacerbating environmental decline [22–25]. Conversely, renewable energy is vital for enhancing environmental quality, as it generates considerably lower emissions than fossil fuels. Its implementation aids in decreasing pollution levels and alleviating greenhouse gas concentrations, positioning it as a more sustainable energy option [24–27]. Moreover, economic growth and capital formation, although crucial for progress, can place strain on the environment by encouraging industrial operations, raising energy usage, and broadening infrastructure, especially in emerging economies [12, 25, 28, 29].

As reported by the Center for Research on the Epidemiology of Disasters (CRED) [30], the frequency of natural disasters has risen sharply by 46% over the past three decades, from 303 events in 1990 to 444 in 2019. This increase has led to severe consequences, including loss of life, injuries, and economic disruption. Financially, disaster-related damages have more than doubled, surging from USD 49.78 million in 1990 to USD 100.94 million in 2019, with an average annual growth of 2.38% [18, 30]. Previous studies have primarily examined the social and economic impacts of natural disasters, with limited focus on environmental effects. However, disasters can lower overall consumption [31–33], potentially reducing energy use and CO_2 emissions [34]. Lee et al. [35], analyzing data from 123 countries (1990–2015), found that disasters significantly reduce oil, renewable, and nuclear energy consumption, linking this to consumption poverty [36, 37]. Reduced transport activity may also drive energy savings. Conversely, Doytch & Klein [38], using data from 80 countries (1961–2011), reported a positive link between disasters and energy use, varying by energy type and income level. High-income countries saw increased renewable use, while middle- and low-income nations experienced higher residential and industrial consumption. Similarly, Idroes et al. [39], using Autoregressive Distributed Lag (ARDL) methods for Indonesia over the period 1980–2021, found that natural disasters, non-renewable energy consumption, and economic growth significantly increase CO_2 emissions, while renewable energy usage contributes to their reduction. The study also identified a unidirectional causal relationship from natural disasters and renewable energy to CO_2 emissions. Furthermore, Cao et al. [19] employed the Nonlinear Autoregressive Distributed Lag (NARDL) model to analyze data from China spanning 2000 to 2020, uncovering a significant

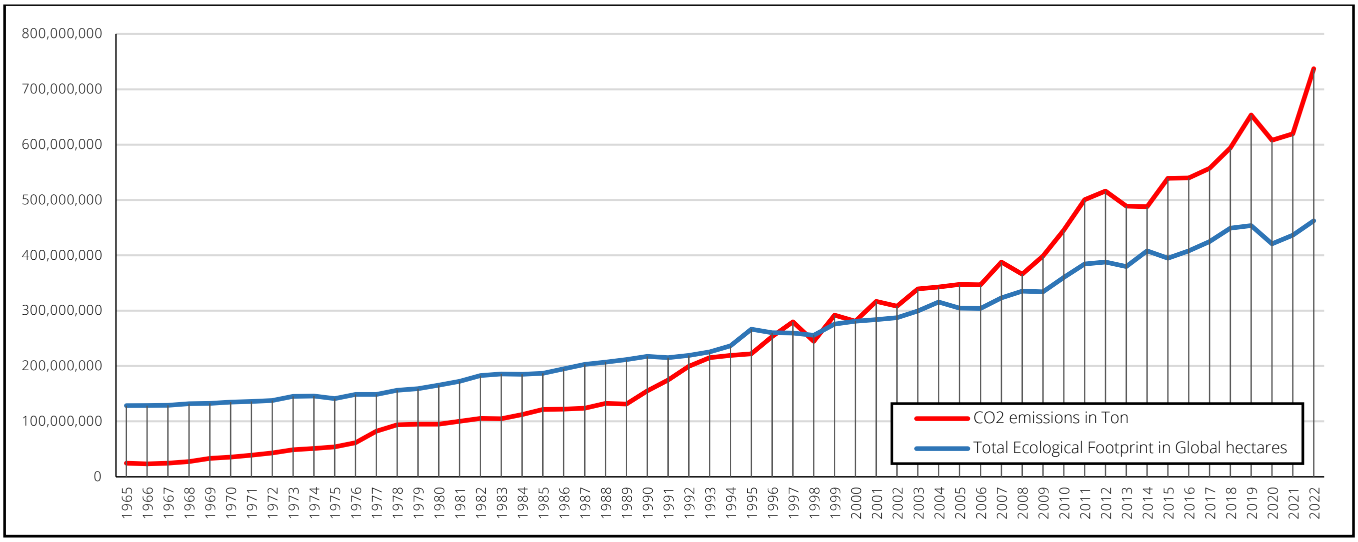


Figure 1. Trends in CO_2 emissions and ecological footprint in Indonesia from 1965 to 2022 [13, 14].

long-term nonlinear relationship among carbon emissions, new energy consumption, and direct economic losses resulting from natural disasters. Their findings indicate a U-shaped correlation between disaster-related losses and carbon emissions: when losses fall below a certain threshold, emissions are significantly reduced, whereas smaller-scale losses tend to increase emissions.

The type of energy utilized significantly influences environmental quality, often measured through indicators such as CO_2 emissions and ecological footprint [40, 41]. Non-renewable energy sources, particularly fossil fuels like coal, oil, and natural gas, are major contributors to environmental degradation, leading to increased CO_2 emissions and a larger ecological footprint due to extraction, processing, and combustion. The negative environmental impact of non-renewable energy has been confirmed by several researchers, including Pata [42], Acaroğlu et al. [41] and Idroes et al. [43], who found that fossil fuel consumption significantly increases CO_2 emissions. Similarly, studies by Pata [42], Ehigiamusoe et al. [44] and Idroes et al. [43] highlight its role in expanding the ecological footprint. In contrast, renewable energy sources such as solar, wind, hydro, and biomass are generally associated with lower emissions and a reduced environmental impact. This has been supported by research from Waheed et al. [45], Pata [42], Kuldasheva & Salahodjaev [46] and Sahoo et al. [47], who observed that renewables contribute to lower CO_2 emissions, while Pata [42], Ehigiamusoe et al. [44], Idroes et al. [43], Liu et al. [48] and Sikdar et al. [49] found a positive effect in reducing the ecological footprint. By replacing fossil fuels, renewable energy helps decrease greenhouse gas emissions and alleviates pressure on natural ecosystems, thereby improving overall environmental quality. Consequently, the transition to renewable energy is considered essential for reducing carbon intensity and promoting sustainable ecological outcomes [29, 40, 41].

Focusing on Indonesia, Rahman et al. [50] found that air quality in the country is significantly impacted by frequent forest fires and volcanic eruptions, both of which are linked to deforestation and natural disasters. Their study, covering 30 Indonesian cities from 2002 to 2019, revealed that economic growth is associated with worsening air quality, rejecting the Environmental Kuznets Curve (EKC) hypothesis. Furthermore, the study highlighted the significant contribution of forest fires to pollution, with a partial Benefit-Cost Analysis (BCA) estimating that reducing forest fires by 1% could yield health and agricultural benefits ranging from US$17 million to US$145 million. In another study, Kurniawan et al. [51] used Dynamic ARDL to analyze data from 1991 to 2020 and found that forest and land fires increase temperatures, contributing to climate change in Indonesia. Additionally, Idroes et al. [39] examined the relationship between natural disasters, energy consumption, and CO_2 emissions in Indonesia from 1980 to 2021. Using ARDL, with robustness checks through Fully Modified Ordinary Least Squares (FMOLS), Dynamic Ordinary Least Squares (DOLS), and Canonical Cointegrating Regression (CCR), their study found that natural disasters, non-renewable energy, and economic growth increase CO_2 emissions, while renewable energy reduces them.

To the best of the author's knowledge, no previous research has thoroughly explored the dynamic impacts of natural disasters, fossil fuel consumption, renewable energy consumption, economic growth, and capital formation on environmental quality in Indonesia using

Table 1. Variable description and data sources.

Variable	Symbol	Measurement Unit	Source
CO_2 emissions	CO2	Metric tons	OWID [13]
Ecological footprint	EFP	Global hectares (gha)	GFN [14]
Natural disasters	ND	Total number of deaths	OWID [62]
Fossil fuel	FF	Terawatt-hours (TWh)	OWID [63]
Renewable energy	RE	Terawatt-hours (TWh)	OWID [64]
Economic growth	GDP	Constant Local Currency Units (LCU)	WDI [65]
Capital formation	CF	Constant Local Currency Units (LCU)	WDI [65]

both CO_2 emissions and the ecological footprint as indicators. This study fills that gap by employing the ARDL model, reinforced with DOLS, followed by Granger causality tests over the period 1965–2022. The findings provide empirical insights into the short- and long-run relationships among these variables and contribute to a deeper understanding of the environmental consequences by offering a comprehensive explanation with CO_2 emissions and the ecological footprint as representations of environmental quality.

2. Materials and Methods

2.1. Data

This study investigates the dynamic impact of natural disasters, fossil fuel consumption, renewable energy use, economic growth, and capital formation on CO_2 emissions and the ecological footprint in Indonesia from 1965 to 2022. The data is transformed into a biannual (twice-a-year) format to increase the number of observations and improve the robustness of the time series analysis. CO_2 emissions, measured in metric tons, and the ecological footprint, measured in global hectares (gha), are used as proxies to represent environmental quality. These data were obtained from Our World in Data (OWID) [13] and the Global Footprint Network (GFN) [14]. Data on natural disasters, including total deaths caused by droughts, floods, earthquakes, extreme weather events, extreme temperatures, volcanic activity, wildfires, glacial hazards, etc., were sourced from OWID [62]. Information on fossil fuel and renewable energy consumption, both measured in terawatt-hours (TWh), was also obtained from OWID [63, 64]. Economic growth, represented by GDP, and capital formation, both measured in constant local currency units (LCU), were retrieved from the World Bank's World Development Indicators (WDI) [65]. Table 1 presents the variable descriptions and data sources used in this study.

Environmental quality in this study is represented by two key indicators: CO_2 emissions and ecological footprint [43, 52]. CO_2 emissions serve as a direct measure of atmospheric pollution resulting primarily from fossil fuel combustion and industrial activity, making them a widely used proxy for environmental degradation and climate change [53, 54]. On the other hand, the ecological footprint offers a broader perspective by quantifying the pressure human activities place on ecosystems, including resource consumption and waste generation relative to the Earth's biocapacity [55, 56]. Together, these indicators provide a more comprehensive assessment of environmental quality, capturing both the immediate impacts of emissions and the long-term sustainability of resource use.

Furthermore, the independent variables in this study are natural disasters, fossil fuel consumption, renewable energy use, economic growth, and capital formation, each selected for their relevance to environmental quality. Natural disasters are included due to their disruptive effects on infrastructure, energy use, and economic activity, which can influence environmental outcomes. This variable has been used in several studies, such as Lee et al. [35], Doytch & Klein [38], Idroes et al. [39], Cao et al. [19] and Dou et al. [18], to analyze its environmental impact. Fossil fuel consumption is a major contributor to CO_2 emissions and is widely recognized as a driver of environmental degradation; researchers like Pata [42], Acaroğlu et al. [41], Idroes et al. [43] and Ehigiamusoe et al. [44] have highlighted its significance. Renewable energy is incorporated for its potential to reduce emissions and support sustainable development, as shown in studies by Waheed et al. [45], Pata [42], Kuldasheva & Salahodjaev [46] and Sahoo et al. [47]. Economic growth reflects the scale of economic activity, which may either increase or reduce environmental harm depending on the development stage; this relationship has been extensively explored by Maulidar et al. [57], Ansari [58] and Erdoğan et al. [59]. Capital formation captures investment in infrastructure and productive assets, which can affect emissions based on the nature of the investments. Maulidar et al. [28], Chekouri et al. [60], and Aderinto & Ogunro [61], among others, have examined the environmental implications of capital accumulation.

2.2. Mathematical Function and Empirical Model

This study adopts an empirical model previously investigated by Sahoo et al. [47], Idroes et al. [43], Waheed et al. [45], Liu et al. [48], Ehigiamusoe et al. [44], Hardi et al. [66] and Acaroğlu et al. [41] to analyze the influence of economic factors on the environment. A key feature of their approach is the simultaneous assessment of CO_2 emissions and ecological footprints, providing a holistic perspective on environmental impact within a single framework. Building on this foundation, we modified our model to capture the dynamic effects of natural disasters, fossil fuel consumption, renewable energy, economic growth, and capital formation on CO_2 emissions and the ecological footprint. The initial functional form is outlined in Equations 1 and 2.

$$CO2_t = f(ND_t, FF_t, RE_t, GDP_t, CF_t) \tag{1}$$

$$EFP_t = f(ND_t, FF_t, RE_t, GDP_t, CF_t) \tag{2}$$

Where $CO2$ and EFP represent carbon dioxide emissions and the ecological footprint, respectively. ND stands for natural disasters, FF denotes fossil fuel consumption, RE represents renewable energy, GDP signifies economic growth, and CF refers to capital formation. Prior to the analysis, all variables are transformed into their logarithmic forms to simplify relationships and enhance interpretability. Equations 1 and 2 are reformulated into log-linear econometric models, as illustrated in Equations 3 and 4.

$$lnCO2_t = \psi_0 + \psi_1 lnND_t + \psi_2 lnFF_t + \psi_3 lnRE_t + \psi_4 lnGDP_t + \psi_5 lnCF_t + \varepsilon_t \tag{3}$$

$$lnEFP_t = \psi_0 + \psi_1 lnND_t + \psi_2 lnFF_t + \psi_3 lnRE_t + \psi_4 lnGDP_t + \psi_5 lnCF_t + \varepsilon_t \tag{4}$$

Where ψ_0 represents the intercept, while ε_t denotes the error term. The coefficients ψ_1 to ψ_5 correspond to the estimated parameters, which may exhibit either positive or negative signs.

2.3. Methods

2.3.1. Autoregressive Distributed Lag (ARDL)

The ARDL model is a widely utilized econometric technique designed to estimate both short-run dynamics and long-run equilibrium relationships among time series variables, regardless of whether the variables are integrated at level I(0), first difference I(1), or a combination of both [11, 41, 67]. By incorporating appropriate lag structures of both the dependent and independent variables, the ARDL approach effectively captures the temporal behavior and interactions among variables [28, 29, 68]. Additionally, the inclusion of the error correction term (ECT) in the model allows for measuring the speed at which deviations from the long-run equilibrium are corrected over time. The ARDL method is particularly suitable for small sample sizes and provides a robust framework for examining the dynamic linkages between economic and environmental indicators. Numerous studies have employed the ARDL approach in similar contexts, including Baloch et al. [69], Supruń & Myszczyszyn [70], Idroes et al. [29], Maulidar et al. [28] and Arshad et al. [71], highlighting its relevance and applicability in empirical research. The ARDL model applied in this study is represented in Equations 5 and 6.

Where t denotes the study period and Δ represents the first difference operator. The coefficients ϕ_1 to ϕ_6 indicate the long-run effects, whereas φ_1 to φ_6 represent the short-run relationships. The parameter λ denotes the error correction term (ECT), which captures the speed of adjustment back to long-run equilibrium. Lastly, q and p refer to the optimal lag lengths selected for the model. Prior to ARDL estimation, several preliminary tests were conducted to ensure the suitability of the data and model specification. These include unit root tests, lag length selection, and the ARDL bounds test for cointegration.

$$\Delta lnCO2_t = \beta_0 + \sum_{i=0}^{q} \varphi_1 \Delta lnCO2_{t-i} + \sum_{i=0}^{p} \varphi_2 \Delta lnND_{t-i} + \sum_{i=0}^{p} \varphi_3 \Delta lnFF_{t-i} + \sum_{i=0}^{p} \varphi_4 \Delta lnRE_{t-i} + \sum_{i=0}^{p} \varphi_5 \Delta lnGDP_{t-i} + \sum_{i=0}^{p} \varphi_6 \Delta lnCF_{t-i} + \lambda ECT_{t-1} + \phi_1 lnCO2_{t-1} + \phi_2 lnND_{t-1} + \phi_3 lnFF_{t-1} + \phi_4 lnRE_{t-1} + \phi_5 lnGDP_{t-1} + \phi_6 lnCF_{t-1} + \varepsilon_t \tag{5}$$

$$\Delta lnEFP_t = \beta_0 + \sum_{i=0}^{q} \varphi_1 \Delta lnEFP_{t-i} + \sum_{i=0}^{p} \varphi_2 \Delta lnND_{t-i} + \sum_{i=0}^{p} \varphi_3 \Delta lnFF_{t-i} + \sum_{i=0}^{p} \varphi_4 \Delta lnRE_{t-i} + \sum_{i=0}^{p} \varphi_5 \Delta lnGDP_{t-i} + \sum_{i=0}^{p} \varphi_6 \Delta lnCF_{t-i} + \lambda ECT_{t-1} + \phi_1 lnEFP_{t-1} + \phi_2 lnND_{t-1} + \phi_3 lnFF_{t-1} + \phi_4 lnRE_{t-1} + \phi_5 lnGDP_{t-1} + \phi_6 lnCF_{t-1} + \varepsilon_t \tag{6}$$

2.3.1.1. Unit Root Tests

The Augmented Dickey-Fuller (ADF) and Phillips-Perron (P-P) tests were applied to examine the stationarity of each variable [72, 73]. These tests help determine the order of integration, ensuring that none of the series are integrated of order two, I(2), which is a key requirement for the ARDL approach. The results confirm that all variables are either stationary at level, I(0), or at first difference, I(1), thereby justifying the use of the ARDL model.

2.3.1.2. Lag Length Selection

The optimal lag length was selected based on the Akaike Information Criterion (AIC), which balances goodness of fit and model parsimony. The chosen lag structure ensures that the ARDL model adequately captures the short-run and long-run dynamics of the variables under investigation [29, 74, 75].

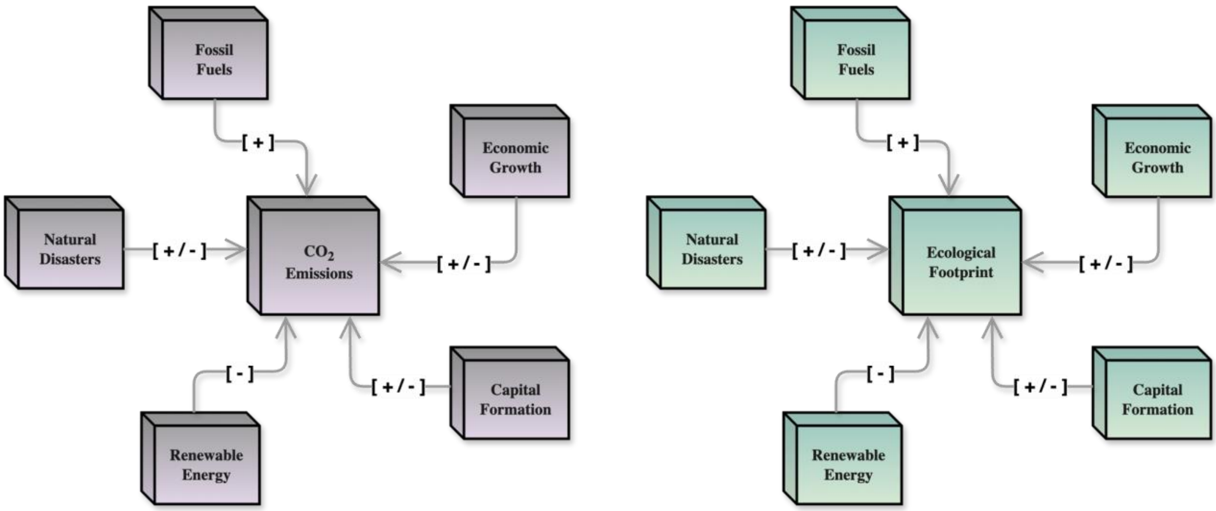


Figure 2. Conceptual framework.

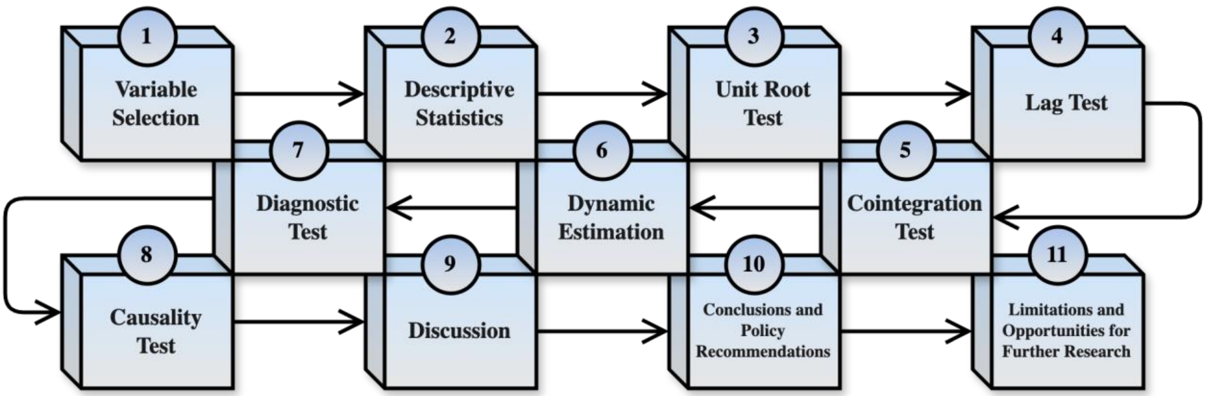


Figure 3. Flow stages of the analysis.

2.3.1.3. ARDL Bounds Test

The ARDL bounds testing procedure was employed to assess the existence of long-run relationships among the variables. The null hypothesis of no cointegration is rejected if the calculated F-statistic exceeds the upper critical bound [76]. The test results confirm cointegration in both models, supporting the presence of stable long-run relationships.

2.3.2. Dynamic Ordinary Least Squares (DOLS)

The DOLS method is widely applied for estimating models involving non-stationary time series data. Originally introduced by Stock & Watson [77], DOLS is especially effective for examining relationships among variables that exhibit unit roots, as it ensures consistent estimation of long-run parameters. This approach enhances the conventional OLS technique by including lagged and lead differences of the explanatory variables, thereby addressing the challenges of non-stationarity and minimizing the risk of spurious regression. One of the key strengths of DOLS is its ability to yield efficient and reliable estimates even when the data are integrated, making it particularly suitable for capturing long-term dynamics and persistent structural changes [78–80]. As such, DOLS serves as a robust method for validating the long-run coefficients obtained from ARDL models.

2.3.3. Granger Causality

The Granger causality test is a simple and widely used method for identifying causal relationships between two time series variables. Based on the framework developed by Granger [81], it evaluates whether past values of one variable improve the prediction of another beyond its own lags. Its main advantage lies in its ease of implementation and interpretation, allowing researchers to assess directional causality without the need for a full multivariate model.

2.4. Conceptual Framework

This study examines the impact of key macroeconomic factors on two environmental indicators: CO_2 emissions and ecological footprint. Figure 2 outlines a conceptual framework in which fossil fuels, natural disasters, renewable energy, economic growth, and capital

Table 2. Descriptive statistics.

Variable	Mean	Median	Max.	Min.	Std. Dev.	Obs.
lnCO2	18.9665	19.2003	20.481	16.9665	0.9920	116
lnEFP	19.2806	19.2514	19.9696	18.6714	0.4088	116
lnND	5.4491	5.5419	12.1252	-0.9261	1.9996	116
lnFF	6.3551	6.6228	7.9186	4.3148	1.0900	116
lnRE	3.1291	3.3549	5.6664	1.1400	1.2653	116
lnGDP	35.6461	35.8023	37.0141	34.0305	0.8749	116
lnCF	34.2181	34.5342	35.8531	31.4433	1.2385	116

Table 3. Unit root test results.

Variable	Level				1st Diff.			
	Intercept		*Trend & Intercept*		*Intercept*		*Trend & Intercept*	
	t-stat.	**Prob.**	**t-stat.**	**Prob.**	**t-stat.**	**Prob.**	**t-stat.**	**Prob.**
ADF								
lnCO2	-1.9620	0.3032	-2.2601	0.4516	-3.1989**	0.0227	-3.6382**	0.0312
lnEFP	0.2732	0.9758	-3.6748**	0.0284	-4.5756***	0.0003	-4.5624***	0.0020
lnND	-2.7169	0.0746	-3.5104**	0.0435	-4.1647***	0.0012	-4.1093***	0.0084
lnFF	-1.9081	0.3276	-1.6977	0.7460	-3.7849***	0.0041	-4.0618***	0.0095
lnRE	0.5529	0.9878	-4.0869***	0.0089	-3.3851**	0.0137	-4.1025***	0.0085
lnGDP	-1.7657	0.3957	-1.8913	0.6523	-3.9401***	0.0025	-4.2602***	0.0052
lnCF	-2.4489	0.1311	-2.6109	0.2765	-3.3968**	0.0131	-4.1063***	0.0083
P-P								
lnCO2	-1.5783	0.4904	-1.7304	0.7314	-6.1681***	0.0000	-5.9274***	0.0000
lnEFP	0.7456	0.9927	-3.3633	0.0616	-6.8541***	0.0000	-6.9376***	0.0000
lnND	-4.2291***	0.0009	-3.6848**	0.0273	-11.049***	0.0000	-10.880***	0.0000
lnFF	-1.5416	0.5091	-0.9077	0.9509	-4.2686***	0.0008	-4.2308***	0.0056
lnRE	0.2804	0.9763	-2.0358	0.5754	-6.9677***	0.0000	-6.9831***	0.0000
lnGDP	-1.7820	0.3878	-1.4329	0.8462	-4.9960***	0.0001	-4.8876***	0.0006
lnCF	-2.7450	0.0697	-1.9073	0.6443	-4.8957***	0.0001	-4.6820***	0.0013

Note: ** and *** indicates significant level in 5% and 1%, respectively.

formation influence both indicators. A positive sign (+) indicates an increasing effect, while a negative sign (–) reflects a reducing effect. In the left panel, CO_2 emissions are primarily driven by fossil fuel use (+), while renewable energy reduces emissions (–). Economic growth, capital formation, and natural disasters may have mixed effects (+/–), depending on context. The right panel shifts to ecological footprint, a broader measure of environmental impact. While the same variables apply, their effects vary: fossil fuels increase the footprint (+), renewable energy reduces it (–), and economic growth, capital formation, and natural disasters may have mixed effects (+/–).

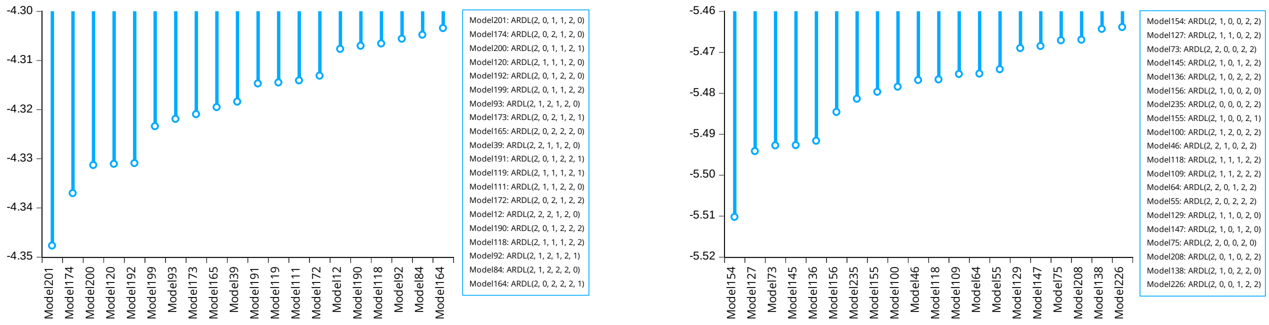
2.5. Workflow of the Study

The flow stages in Figure 3 outline the step-by-step process of the econometric analysis. It begins with variable selection (Step 1), followed by descriptive statistics (Step 2), stationarity tests using ADF and PP methods (Step 3), and optimal lag selection (Step 4). Cointegration is tested using the ARDL bounds approach (Step 5), followed by dynamic estimation with ARDL and DOLS models (Step 6). Diagnostic tests are conducted (Step 7), and Granger causality analysis is performed (Step 8). Results are interpreted in the discussion (Step 9), followed by conclusions and policy recommendations (Step 10), and consideration of limitations and future research directions (Step 11).

3. Results and Discussion

3.1. Descriptive Statistics

Table 2 presents the descriptive statistics for key logarithmic-transformed variables across 116 observations. CO_2 has a mean of 18.97 and a median of 19.20, with a minimum value of 16.97 and a maximum of 20.48, indicating slight left skewness. EFP shows a mean of 19.28 and a median of 19.25, ranging from a minimum of 18.67 to a maximum of 19.97. ND exhibits high variability, with a mean of 5.45, a minimum of -0.93, and a maximum of 12.13. FF has a mean of 6.36 and a median of 6.62, with values ranging from 4.31 to 7.92. RE records a mean of 3.13 and a median of 3.35, with a minimum of 1.14 and a maximum of 5.67. GDP ranges from 34.03 to 37.01 (mean: 35.65; median: 35.80), while CF ranges from 31.44 to 35.85 (mean: 34.22; median: 34.53), indicating relative economic stability. Logarithmic transformation improves normalization and comparability across variables.



(a) **(b)**

Figure 4. Lag selections: (a) for the CO_2 model (2, 0, 1, 1, 2, 0) and (b) for the EFP model (2, 1, 0, 0, 2, 2).

Table 4. ARDL bounds test results.

F-bounds test			*Null Hypothesis: No levels relationship*		
Model	**Test Stat.**	**Value**	**Signif.**	**I(0)**	**I(1)**
CO_2	F-stat.	7.0769	10%	2.08	3
	K	5	5%	2.39	3.38
EFP	F-stat.	6.8577	2.5%	2.7	3.73
	k	5	1%	3.06	4.15

3.2. Unit Root Test

Table 3 presents the unit root test results using the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests, assessing stationarity at both level and first difference. At the level form, in both intercept and trend & intercept specifications, all variables fail to reject the null hypothesis of a unit root in both ADF and PP tests, indicating that CO_2, EFP, ND, FF, RE, GDP, and CF are non-stationary. The only exception is ND in the PP test, which is significant at 1%, suggesting stationarity. However, after first differencing, in both intercept and trend & intercept specifications, all variables become stationary at either the 5% or 1% significance level across both ADF and PP tests. This confirms that all variables are integrated of order one (I(1)), meaning they exhibit unit roots at the level form but achieve stationarity after first differencing.

3.3. Lag Selection Test

Figure 4 presents the lag selection results for the ARDL models. Figure 4a identifies the optimal ARDL model for CO_2 as ARDL (2, 0, 1, 1, 2, 0), while Figure 4b selects ARDL (2, 1, 0, 0, 2, 2) for EFP. The models were chosen based on the lowest information criteria values, with the plotted models ranked accordingly. The selected lag structures will be used for further analysis.

3.4. ARDL Bound Test

Table 4 presents the ARDL bounds test results for CO_2 and EFP models, assessing the presence of a long-run relationship. Both models pass the 5% and 1% significance levels, as their F-statistics (7.0769 for CO_2 and 6.8577 for EFP) exceed the upper bound critical values of 3.38 (5%) and 4.15 (1%). These results provide strong evidence of cointegration, confirming a stable long-run relationship in both models.

3.5. ARDL Estimation Results

3.5.1. ARDL CO_2 Emissions Model

Table 5 presents the ARDL estimation results for the CO_2 model, with CO_2 emissions as the dependent variable, capturing both long-run and short-run impacts. In the long run, ND has a positive impact on CO_2, where a 1% increase in ND increases CO_2 by 0.0108%. FF also has a positive impact, as a 1% increase raises CO_2 by 0.4019%. Similarly, GDP positively affects CO_2, with a 1% increase leading to a 0.8803% rise in CO_2. Conversely, RE has a negative impact, as a 1% increase in RE reduces CO_2 by 0.0750%. CF has a negative coefficient but is statistically insignificant in the long run. Furthermore, in the short run, CO_2 exhibits persistence, with its lagged value CO_2(-1) showing a positive impact of 0.3994%. FF has a positive effect, where a 1% increase leads to a 0.7748% rise in CO_2. GDP also positively impacts CO_2, with a 1% increase raising CO_2 by 0.4957%. However, lagged GDP has a negative impact, as a 1% increase in GDP(-1) decreases CO_2 by 0.6160%. RE continues to show a negative effect, where a 1% increase lowers CO_2 by 0.0753%. The ECT in the CO_2 model confirms a stable long-run relationship, with 26.34% of equilibrium restored each period.

Table 5. ARDL results for the CO_2 emissions model.

Variable	Coeff.	Std. Err.	t-Stat.	Prob.
Long-run				
lnND	0.0108*	0.0061	1.7617	0.0811
lnFF	0.4019***	0.0658	6.1060	0.0000
lnRE	-0.0750**	0.0289	-2.5932	0.0109
lnGDP	0.8803***	0.1383	6.3639	0.0000
lnCF	-0.1115	0.0764	-1.4593	0.1475
C	-10.9688	3.0011	-3.6549	0.0004
Short-run				
ΔlnCO2(-1)	0.3994***	0.0660	6.0556	0.0000
ΔlnFF	0.7748***	0.0805	9.6271	0.0000
ΔlnRE	-0.0753***	0.0168	-4.4945	0.0000
ΔlnGDP	0.4957***	0.1637	3.0282	0.0031
ΔlnGDP(-1)	-0.6160***	0.1611	-3.8227	0.0002
ECT(-1)	-0.2634***	0.0364	-7.2424	0.0000
R^2	0.9993			
Adj. R^2	0.9993			

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 6. ARDL results for the EFP model.

Variable	Coeff.	Std. Err.	t-Stat.	Prob.
Long-run				
lnND	-0.0009	0.0027	-0.3568	0.7220
lnFF	0.0311	0.0285	1.0898	0.2784
lnRE	-0.0191	0.0127	-1.4965	0.1376
lnGDP	0.8428***	0.0576	14.643	0.0000
lnCF	-0.2781***	0.0327	-8.5014	0.0000
C	-1.3676	1.2593	-1.0860	0.2801
Short-run				
ΔlnEFP(-1)	0.5478***	0.0720	7.6137	0.0000
ΔlnND	0.0019**	0.0009	2.1451	0.0343
ΔlnGDP	0.5307***	0.1113	4.7695	0.0000
ΔlnGDP(-1)	-0.5001***	0.1279	-3.9107	0.0002
ΔlnCF	-0.0842**	0.0402	-2.0960	0.0386
ΔlnCF(-1)	0.1011**	0.0430	2.3523	0.0206
ECT(-1)	-0.3400***	0.0477	-7.1313	0.0000
R^2	0.9988			
Adj. R^2	0.9987			

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

3.5.2. ARDL EFP Model

Table 6 presents the ARDL estimation results for the EFP model, with EFP as the dependent variable, capturing both long-run and short-run impacts. In the long run, GDP has a positive impact on EFP, where a 1% increase in GDP leads to a 0.8428% rise in EFP. CF has a negative impact, as a 1% increase decreases EFP by 0.2781%. However, ND, FF, and RE show no significant impact on EFP in the long run. Furthermore, in the short run, lagged EFP(-1) has a positive effect, where a 1% increase raises EFP by 0.5478%. ND also has a positive impact, as a 1% increase leads to a 0.0019% rise in EFP. GDP positively influences EFP, with a 1% increase resulting in a 0.5307% rise in EFP. However, lagged GDP(-1) has a negative effect, where a 1% increase in GDP(-1) decreases EFP by 0.5001%. CF negatively impacts EFP, as a 1% increase leads to a 0.0842% reduction, but its lagged value CF(-1) has a positive impact of 0.1011%. The ECT in the EFP model confirms a stable long-run relationship, with 34% of equilibrium restored each period.

3.6. Robustness Check with DOLS

The robustness test results using DOLS, as presented in Table 7, confirm the consistency of the findings previously obtained from the ARDL model for both the CO_2 and EFP models. Each independent variable's coefficient aligns with the ARDL results, reinforcing the reliability of the estimated relationships. This consistency strengthens the argument that the selected variables have a stable and significant impact on environmental quality across different estimation techniques.

3.7. The Diagnostic Test

Table 8 presents the diagnostic test results for the CO_2 and EFP models, confirming that both models are statistically robust and well specified. The high R^2 and

Table 7. DOLS robustness test results.

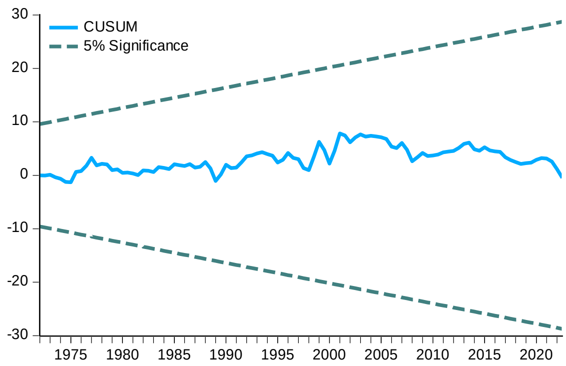
Variable	Coeff.	Std. Err.	t-Stat.	Prob.
CO_2 model				
lnND	0.0016	0.0081	0.1946	0.8462
lnFF	0.4275***	0.0630	6.7885	0.0000
lnRE	-0.0820***	0.0243	-3.3793	0.0011
lnGDP	0.8977***	0.1105	8.1218	0.0000
lnCF	-0.1228*	0.0690	-1.7790	0.0790
C	-11.2805	2.4321	-4.6382	0.0000
R^2	0.9983			
Adj. R^2	0.9976			
EFP model				
lnND	-0.0095**	0.0046	-2.0524	0.0434
lnFF	0.0649*	0.0360	1.8038	0.0750
lnRE	-0.0200	0.0139	-1.4421	0.1532
lnGDP	0.8267***	0.0632	13.0895	0.0000
lnCF	-0.2906***	0.0394	-7.3705	0.0000
C	-0.5441	1.3897	-0.3915	0.6965
R^2	0.9966			
Adj. R^2	0.9953			

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

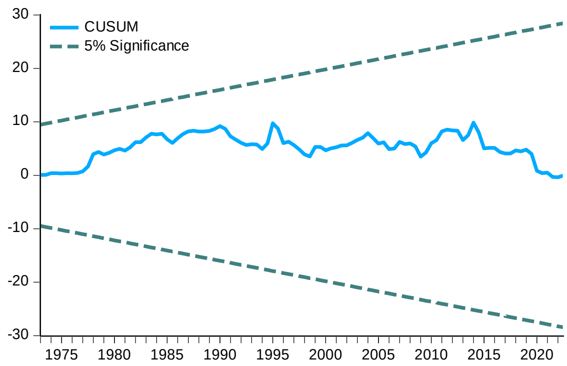
Table 8. The result of the diagnostic test.

Diagnostic tests	CO_2 Model		EFP Model		Decision
	Coeff.	**Prob.**	**Coeff.**	**Prob.**	
R^2	> 0.9993	-	> 0.9988	-	The model is well fitted
Adj. R^2	> 0.9993	-	> 0.9987	-	The model is well fitted
CUSUM	-	< 0.05	-	< 0.05	The model is stable
B-G LM test	3.2100	0.0762	3.5701	0.0617	No serial correlation exists
Harvey test	1.6308	0.1011	1.1889	0.3012	No heteroscedasticity exists
ARCH test	0.1105	0.7402	0.0030	0.9562	No heteroscedasticity exists
Ramsey test	1.7175	0.1848	0.3591	0.7203	The model is properly specified

Note: B-G refers to the Breusch-Godfrey test, and ARCH refers to the Autoregressive Conditional Heteroskedasticity test.



(a)



(b)

Figure 5. The parameters stability test with CUSUM for CO_2 model (a) and EFP model (b).

adjusted R^2 values, each exceeding 0.99, indicate an excellent model fit, suggesting that the independent variables explain nearly all variations in the dependent variables. The CUSUM test results, illustrated in Figure 5a-b, confirm the stability of both models over time. The Breusch-Godfrey (B-G LM) test shows no evidence of serial correlation, while the Harvey and ARCH tests indicate the absence of heteroscedasticity in both models. Additionally, the Ramsey RESET test verifies that the models are correctly specified, with no major functional form misspecifications. Overall, these diagnostic checks validate the reliability and consistency of the ARDL estimation results applied in this study.

3.8. Granger Causality Test

The Granger causality test results presented in Table 9 reveal several directional relationships among the variables in both the CO_2 and EFP models. In the CO_2

Table 9. Granger causality test results.

CO_2 model			EFP model		
Null Hypothesis	**F-Stat.**	**Prob.**	**Null Hypothesis**	**F-Stat.**	**Prob.**
ND does not Granger Cause CO2	0.5495	0.5788	ND does not Granger Cause EFP	1.0890	0.3402
CO2 does not Granger Cause ND	4.9142***	0.0090	EFP does not Granger Cause ND	3.9455**	0.0222
FF does not Granger Cause CO2	1.1152	0.3316	FF does not Granger Cause EFP	2.0106	0.1388
CO2 does not Granger Cause FF	1.0970	0.3375	EFP does not Granger Cause FF	1.1474	0.3213
RE does not Granger Cause CO2	1.3218	0.2709	RE does not Granger Cause EFP	0.4766	0.6222
CO2 does not Granger Cause RE	2.4622*	0.0900	EFP does not Granger Cause RE	5.2795***	0.0065
GDP does not Granger Cause CO2	4.1335**	0.0186	GDP does not Granger Cause EFP	5.1137***	0.0075
CO2 does not Granger Cause GDP	0.0289	0.9715	EFP does not Granger Cause GDP	0.5801	0.5616
CF does not Granger Cause CO2	1.4433	0.2406	CF does not Granger Cause EFP	2.0216	0.1374
CO2 does not Granger Cause CF	4.7896**	0.0101	EFP does not Granger Cause CF	2.1284	0.1239

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

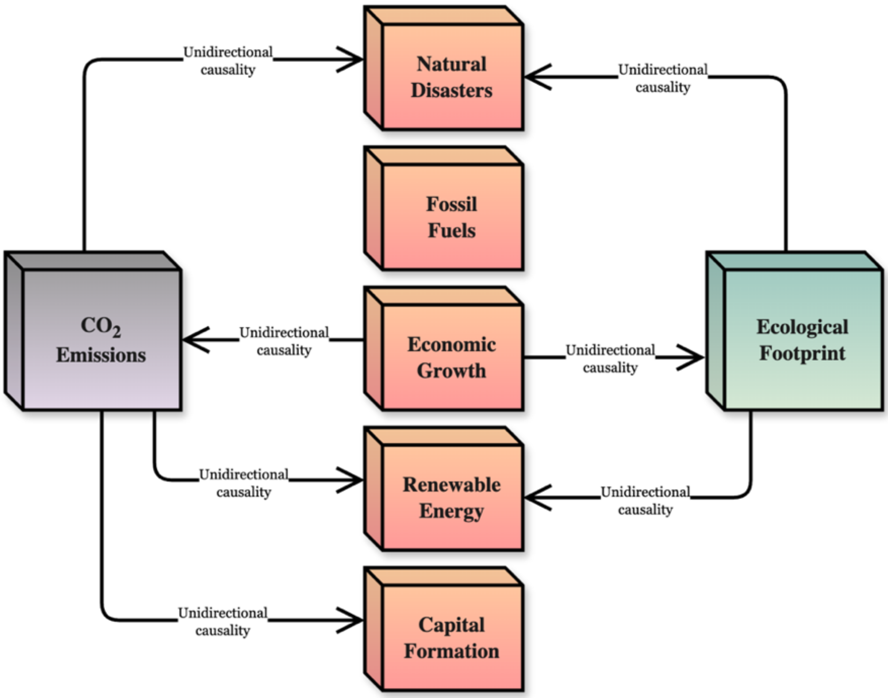


Figure 6. overview of Granger causality test results.

model, unidirectional causality is found running from CO_2 emissions to natural disasters. Additionally, there is evidence of causality from GDP to CO_2 emissions, from CO_2 emissions to renewable energy, and from CO_2 emissions to capital formation. Furthermore, in the EFP model, unidirectional causality is identified from the ecological footprint to natural disasters, from the ecological footprint to renewable energy, and from GDP to the ecological footprint. An overview of the Granger causality is visualized in Figure 6.

3.9. Discussion

This study identifies various impacts of natural disasters, fossil fuels, renewable energy, economic growth, and capital formation on environmental indicators, specifically CO_2 emissions and the ecological footprint. An overview of the long-run impacts is presented and visualized in Figure 7.

Based on the ARDL results, it is evident that, in the long run, natural disasters exert a positive influence on CO_2 emissions, suggesting they contribute to an upward trend in emissions over time. This relationship can be attributed to the context of Indonesia, where natural disasters frequently trigger intensive reconstruction processes that rely heavily on fossil fuels and carbon-intensive sectors such as construction, transportation, and energy production. These sectors become increasingly active during recovery phases, leading to higher emissions. Moreover, the limited integration of green technologies and sustainable practices in post-disaster rebuilding efforts may further intensify environmental degradation in the long term. However, this result is only significant at the 10% level, indicating a relatively weak statistical relationship. This weak significance may be due to the variability in the scale and frequency of natural disasters over time, as not all

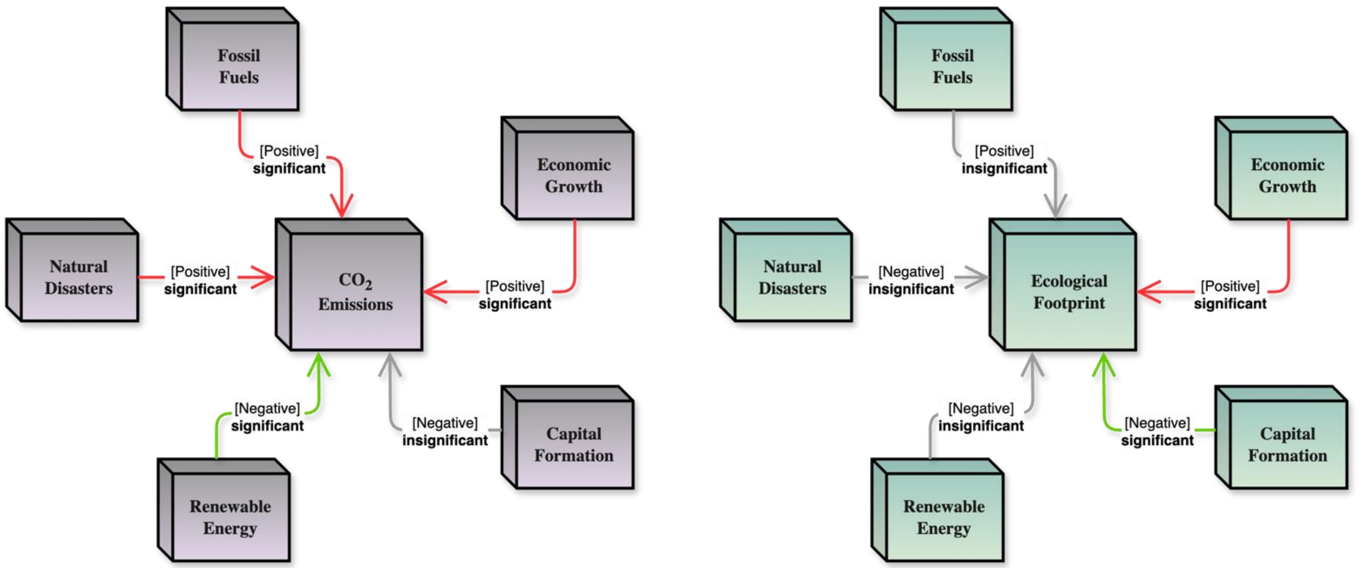


Figure 7. Graphical results of long-term impact for CO_2 and EFP model.

disasters have the same impact on infrastructure, energy demand, or recovery duration. Additionally, improved disaster response mechanisms and international aid in recent years may have mitigated some of the long-term environmental consequences, leading to more mixed outcomes. As such, while natural disasters do contribute to increased CO_2 emissions, their impact appears to be context-dependent and less consistent compared to other drivers such as fossil fuel use or economic growth. These findings are consistent with those of Cao et al. [19], Idroes et al. [39] and Doytch & Klein [38], who observed similar patterns in disaster-affected regions.

In addition to their effect on emissions, natural disasters also impact the ecological footprint. Although the long-run relationship is positive, it is statistically insignificant, indicating that their long-term environmental effect may lessen as recovery stabilizes. In contrast, the short-run impact is both significant and positive, suggesting that disasters impose immediate ecological pressure through increased resource consumption, waste generation, and disruption of sustainable practices. The lack of significance in the long run may be attributed to effective recovery mechanisms, policy interventions, and natural regeneration processes that help mitigate prolonged ecological burdens.

Shifting to the energy dimension, the influence of fossil fuel consumption on environmental quality is both substantial and persistent. The results indicate that fossil fuels have a statistically significant positive effect on CO_2 emissions, meaning they increase atmospheric CO_2 levels in both the short and long run, reaffirming their critical role in greenhouse gas accumulation. However, their impact on the ecological footprint is statistically insignificant in the long run, likely due to the broader scope of the footprint metric, which encompasses factors beyond emissions, such as land use, water consumption, and waste production. This finding highlights the complexity of environmental degradation and reinforces the need to consider multi-dimensional environmental indicators. These results are consistent with those of Pata [42], Acaroğlu et al. [41], Idroes et al. [43] and Ehigiamusoe et al. [44], who emphasized the differentiated environmental effects of fossil fuel use.

In contrast, the long-run results show that renewable energy consumption contributes to a reduction in both CO_2 emissions and the ecological footprint, underlining its importance in promoting environmental sustainability. The increased adoption of renewable sources such as solar, wind, hydro, and bioenergy reduce dependency on fossil fuels and contributes to a decline in emissions over time. Additionally, renewable energy technologies tend to have lower environmental impacts in terms of land use, water usage, and waste generation, collectively easing ecological pressure. These findings support the broader view that renewable energy not only mitigates pollution but also enhances ecological resilience. They are in line with the results reported by Waheed et al. [45], Pata [42], Kuldasheva & Salahodjaev [46], Sahoo et al. [47], Ehigiamusoe et al. [44], Idroes et al. [43] and Liu et al. [48].

Alongside energy consumption, economic growth represented by GDP also emerges as a key driver of environmental change. The findings show that GDP has a positive long-run effect on both CO_2 emissions and the ecological footprint, indicating the environmental trade-offs associated with sustained economic development. In

Indonesia, economic expansion is typically accompanied by intensified industrial activity, increased energy demand, and rapid infrastructure growth, all of which contribute to environmental degradation. These development processes, often concentrated in urban and industrial zones, exert significant pressure on natural resources and ecosystems. While GDP shows varying effects in the short run, possibly influenced by temporary fluctuations, policy measures, or shifts in consumption, the long-term trend highlights a clear conflict between growth and environmental sustainability. These findings are consistent with those of Nathaniel & Khan [82], Ehigiamusoe et al. [44], Idroes et al. [43], Ansari [58] and Maulidar et al. [57], who documented similar patterns in other developing economies.

Furthermore, capital formation, on the other hand, presents a contrasting trend, offering potential for long-term environmental improvement. The results indicate that capital formation has a negative relationship with environmental degradation in the long run, particularly through its significant negative impact on the ecological footprint, although its effect on CO_2 emissions is statistically insignificant. This suggests that investments in infrastructure, technology, and productive capacity, especially when directed toward sustainable and energy-efficient systems, can enhance environmental performance. Over time, such investments can support the transition toward cleaner production and more sustainable consumption patterns. These findings imply that capital formation, when aligned with green development goals, may play a transformative role in reducing long-term ecological pressures. Similar conclusions were drawn by Maulidar et al. [57] and Idroes et al. [83], who emphasized the environmental benefits of sustainability-oriented capital investments.

Finally, the Granger causality results indicate that CO_2 emissions predict natural disasters, renewable energy consumption, and capital formation, while GDP predicts both CO_2 emissions and ecological footprint. Similarly, the ecological footprint predicts natural disasters and renewable energy consumption. These findings suggest that environmental degradation can drive changes in disaster risk, energy transition, and investment, while economic growth remains a key determinant of environmental outcomes, highlighting the need for policies that promote sustainable development.

4. Conclusions and Policy Recommendations

This study investigates the dynamic impact of natural disasters, fossil fuels, renewable energy, economic growth, and capital formation on environmental quality in Indonesia over the period 1965 to 2022 using the ARDL model. Environmental quality is measured through two key indicators: CO_2 emissions and the ecological footprint. The results reveal varying impacts in the short run and long run. In the long run, natural disasters, fossil fuels, and economic growth tend to contribute to environmental degradation, while renewable energy and capital formation show potential in improving environmental quality. In the short run, some variables such as economic growth and natural disasters exhibit dynamic effects, particularly on the ecological footprint. Furthermore, unidirectional causality is found running from CO_2 emissions and ecological footprint to natural disasters and renewable energy. In addition, unidirectional causality is also observed from economic growth to both CO_2 emissions and ecological footprint.

Based on the findings of this study, several policy recommendations are proposed to support Indonesia's transition toward environmental sustainability. Integrating environmentally conscious strategies into disaster recovery and reconstruction is essential, with an emphasis on using low-carbon materials, renewable energy, and sustainable infrastructure to minimize environmental pressures during post-disaster development. Efforts should also focus on accelerating the shift from fossil fuels to renewable energy through targeted incentives, the removal of fossil fuel subsidies, and support for clean energy innovation. To ensure that economic growth does not come at the expense of environmental health, national development planning should prioritize sustainable economic models by promoting green industries, strengthening environmental regulations, and encouraging resource-efficient practices.

Additionally, capital formation should be directed toward investments in clean technologies, energy-efficient infrastructure, and sustainable industrial systems that can help reduce environmental degradation over time. Enhancing environmental resilience is necessary, particularly by improving disaster preparedness, managing resource use efficiently during emergencies, and deploying environmentally sound technologies in response efforts. Furthermore, robust environmental governance is needed through improved data monitoring, inter-agency coordination, and transparent reporting to support evidence-based policymaking. Finally, increasing public awareness through education and outreach can foster sustainable consumption and behavioral change, encouraging collective responsibility for environmental protection. These integrated strategies can help Indonesia achieve a balanced approach to economic development and environmental sustainability.

5. Limitations and Opportunities for Further Research

While this study provides meaningful insights into the long- and short-run impacts of natural disasters, fossil fuel consumption, renewable energy consumption, economic growth, and capital formation on environmental quality in Indonesia, it is not without limitations. The analysis relies on CO_2 emissions and the ecological footprint as proxies for environmental degradation, which, although widely accepted, may not capture other critical dimensions such as deforestation, air and water pollution, or biodiversity loss. Additionally, the use of total deaths to represent the impact of natural disasters may not fully reflect their economic or environmental severity. The ARDL model, though suitable for mixed-order integration and small samples, is inherently linear and may not fully capture asymmetric or distributional effects across different levels of environmental indicators. Future research should consider incorporating additional environmental variables that offer a more holistic view of degradation and sustainability. Moreover, the adoption of more advanced and robust econometric techniques, such as Quantile Regression (QR), Vector Error Correction Models (VECM) or Nonlinear ARDL would provide deeper insights into heterogeneous impacts and improve the robustness of empirical findings. Expanding the scope to regional or sectoral analyses within Indonesia or conducting comparative studies across countries in Southeast Asia could further enrich the understanding of context-specific environmental dynamics and inform more targeted policy interventions.

Author Contributions: Conceptualization, G.M.I., I.S.H. and M.A.; methodology, I.H., Y.H. and C.D.B.; software, G.M.I., M.A. and I.H.; validation, Y.H., A.P., I.S.H. and S.S.; formal analysis, I.H., C.D.B. and Y.H.; investigation, G.M.I., A.P. and S.S.; resources, G.M.I.; data curation, I.H., C.D.B. and Y.H.; writing—original draft preparation, G.M.I., A.P. and S.S.; writing—review and editing, I.S.H., M.A., A.P. and I.H.; visualization, G.M.I., I.S.H. and M.A.; supervision, G.M.I.; project administration, G.M.I.; All authors have read and agreed to the published version of the manuscript.

Funding: There is no institutional funding for this research.

Data Availability Statement: Data will be made available based on request.

Acknowledgments: The authors express their gratitude to their institutions and universities.

Conflicts of Interest: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

1. Saxena, V. (2025). Water Quality, Air Pollution, and Climate Change: Investigating the Environmental Impacts of Industrialization and Urbanization, *Water, Air, & Soil Pollution*, Vol. 236, No. 2, 73. doi:10.1007/s11270-024-07702-4.
2. Bashir, M. F., Pata, U. K., and Shahzad, L. (2025). Linking Climate Change, Energy Transition and Renewable Energy Investments to Combat Energy Security Risks: Evidence from Top Energy Consuming Economies, *Energy*, Vol. 314, 134175. doi:10.1016/j.energy.2024.134175.
3. Ahmed, N., Xinagyu, G., Alnafissa, M., Sikder, M., and Faye, B. (2025). Evaluating the Impact of Sustainable Technology, Resource Utilization, and Climate Change on Soil Emissions: A CS-ARDL Analysis of Leading Agricultural Economies, *Cleaner Engineering and Technology*, Vol. 24, 100869. doi:10.1016/j.clet.2024.100869.
4. Lu, C., and Wang, K. (2023). Natural Resource Conservation Outpaces and Climate Change: Roles of Reforestation, Mineral Extraction, and Natural Resources Depletion, *Resources Policy*, Vol. 86, 104159. doi:10.1016/j.resourpol.2023.104159.
5. Nagarajan, C. D., Afjal, M., and Idroes, G. M. (2024). Distinct Impacts of Frugality on the Intention to Embrace Energy-Efficient and Energy-Generating Products, *International Journal of Energy Sector Management*. doi:10.1108/IJESM-06-2024-0001.
6. Han, Y., Bao, M., Niu, Y., and Rehman, J. ur. (2024). Driving towards Net Zero Emissions: The Role of Natural Resources, Government Debt and Political Stability, *Resources Policy*, Vol. 88, 104479. doi:10.1016/j.resourpol.2023.104479.
7. Rehman, A., Alam, M. M., Ozturk, I., Alvarado, R., Murshed, M., Işık, C., and Ma, H. (2022). Globalization and Renewable Energy Use: How Are They Contributing to Upsurge the CO2 Emissions? A Global Perspective, *Environmental Science and Pollution Research*, Vol. 30, No. 4, 9699–9712. doi:10.1007/s11356-022-22775-6.
8. Li, X., Li, Z., Su, C.-W., Umar, M., and Shao, X. (2022). Exploring the Asymmetric Impact of Economic Policy Uncertainty on China's Carbon Emissions Trading Market Price: Do Different Types of Uncertainty Matter?, *Technological Forecasting and Social Change*, Vol. 178, 121601. doi:10.1016/j.techfore.2022.121601.
9. Hussain, M., Usman, M., Khan, J. A., Tarar, Z. H., and Sarwar, M. A. (2022). Reinvestigation of Environmental Kuznets Curve with Ecological Footprints: Empirical Analysis of Economic Growth and Population Density, *Journal of Public Affairs*, Vol. 22, No. 1. doi:10.1002/pa.2276.
10. Radmehr, R., Shayanmehr, S., Ali, E. B., Ofori, E. K., Jasińska, E., and Jasiński, M. (2022). Exploring the Nexus of Renewable Energy, Ecological Footprint, and Economic Growth through Globalization and Human Capital in G7 Economics, *Sustainability*, Vol. 14, No. 19, 12227. doi:10.3390/su141912227.
11. Hardi, I., Afjal, M., Can, M., Idroes, G. M., Noviandy, T. R., and Idroes, R. (2024). Shadow Economy, Energy Consumption, and Ecological Footprint in Indonesia, *Sustainable Futures*, Vol. 8, 100343. doi:10.1016/j.sftr.2024.100343.
12. Zhang, C., Khan, I., Dagar, V., Saeed, A., and Zafar, M. W. (2022). Environmental Impact of Information and Communication Technology: Unveiling the Role of Education in Developing Countries, *Technological Forecasting and Social Change*, Vol. 178, 121570. doi:10.1016/j.techfore.2022.121570.
13. Our World in Data (OWID). (2024). CO_2 and Greenhouse Gas Emissions, from https://ourworldindata.org/#entries.
14. Global Footprint Network. (2023). Footprint Network Data, from https://data.footprintnetwork.org/#/.
15. Alsaggaf, M. I. (2025). Exploring the Role of Land Utilization, Renewable Energy, and ICT to Counter the Environmental Emission: A Panel Study of Selected G20 and OECD Countries,

Land Degradation & Development, Vol. 36, No. 5, 1707–1723. doi:10.1002/ldr.5458.

16. Kelly, A. M., and Nembot Ndeffo, L. (2025). Understanding the Nexus: Economic Complexity and Environmental Degradation in Sub-Saharan Africa, *Clean Technologies and Environmental Policy*, Vol. 27, No. 1, 423–437. doi:10.1007/s10098-024-02885-0.
17. Zandalinas, S. I., Fritschi, F. B., and Mittler, R. (2021). Global Warming, Climate Change, and Environmental Pollution: Recipe for a Multifactorial Stress Combination Disaster, *Trends in Plant Science*, Vol. 26, No. 6, 588–599. doi:10.1016/j.tplants.2021.02.011.
18. Dou, Y., Shahbaz, M., Dong, K., and Dong, X. (2022). How Natural Disasters Affect Carbon Emissions: The Global Case, *Natural Hazards*, Vol. 113, No. 3, 1875–1901. doi:10.1007/s11069-022-05374-z.
19. Cao, M., Xu, Y., Sun, Y., and Cang, D. (2023). Natural Disasters, Economic Growth, and Carbon Emissions: Empirical Analysis of Chinese Data Based on a Nonlinear Auto-Regressive Distributed Lag Model, *Sustainability*, Vol. 15, No. 21, 15210. doi:10.3390/su152115210.
20. Peduzzi, P. (2019). The Disaster Risk, Global Change, and Sustainability Nexus, *Sustainability*, Vol. 11, No. 4, 957. doi:10.3390/su11040957.
21. Abbass, K., Qasim, M. Z., Song, H., Murshed, M., Mahmood, H., and Younis, I. (2022). A Review of the Global Climate Change Impacts, Adaptation, and Sustainable Mitigation Measures, *Environmental Science and Pollution Research*, Vol. 29, No. 28, 42539–42559. doi:10.1007/s11356-022-19718-6.
22. Voumik, L. C., Islam, M. A., Ray, S., Mohamed Yusop, N. Y., and Ridzuan, A. R. (2023). CO2 Emissions from Renewable and Non-Renewable Electricity Generation Sources in the G7 Countries: Static and Dynamic Panel Assessment, *Energies*, Vol. 16, No. 3, 1044. doi:10.3390/en16031044.
23. Zhang, Y., Li, L., Sadiq, M., and Chien, F. (2023). The Impact of Non-renewable Energy Production and Energy Usage on Carbon Emissions: Evidence from China, *Energy & Environment*, 0958305X2211504. doi:10.1177/0958305X221150432.
24. Holechek, J. L., Geli, H. M. E., Sawalhah, M. N., and Valdez, R. (2022). A Global Assessment: Can Renewable Energy Replace Fossil Fuels by 2050?, *Sustainability*, Vol. 14, No. 8, 4792. doi:10.3390/su14084792.
25. Abbasi, K. R., Shahbaz, M., Zhang, J., Irfan, M., and Alvarado, R. (2022). Analyze the Environmental Sustainability Factors of China: The Role of Fossil Fuel Energy and Renewable Energy, *Renewable Energy*, Vol. 187, 390–402. doi:10.1016/j.renene.2022.01.066.
26. Mahmood, N., Wang, Z., and Hassan, S. T. (2019). Renewable Energy, Economic Growth, Human Capital, and CO2 Emission: An Empirical Analysis, *Environmental Science and Pollution Research*, Vol. 26, No. 20, 20619–20630. doi:10.1007/s11356-019-05387-5.
27. Hardi, I., Idroes, G. M., Hamaguchi, Y., Can, M., Noviandy, T. R., and Idroes, R. (2025). Business Confidence in the Shift to Renewable Energy: A Country-Specific Assessment in Major Asian Economies, *Journal of Economy and Technology*, Vol. 3, 44–68. doi:10.1016/j.ject.2024.08.002.
28. Maulidar, P., Fadila, S., Hafizah, I., Zikra, N., and Idroes, G. M. (2024). Enhancing Environmental Quality: Investigating the Impact of Hydropower Energy Consumption on CO2 Emissions in Indonesia, *Ekonomikalia Journal of Economics*, Vol. 2, No. 1, 53–65. doi:10.60084/eje.v2i1.180.
29. Idroes, G. M., Hardi, I., Hilal, I. S., Utami, R. T., Noviandy, T. R., and Idroes, R. (2024). Economic Growth and Environmental Impact: Assessing the Role of Geothermal Energy in Developing and Developed Countries, *Innovation and Green Development*, Vol. 3, No. 3, 100144. doi:10.1016/j.igd.2024.100144.
30. CRED. (2020). Center for Research on the Epidemiology of Disasters, from https://public.emdat.be/data.
31. Cassar, A., Healy, A., and von Kessler, C. (2017). Trust, Risk, and Time Preferences After a Natural Disaster: Experimental Evidence from Thailand, *World Development*, Vol. 94, 90–105. doi:10.1016/j.worlddev.2016.12.042.
32. Karim, A., and Noy, I. (2016). Poverty and Natural Disasters — a Qualitative Survey of the Empirical Literature, *The Singapore Economic Review*, Vol. 61, No. 01, 1640001. doi:10.1142/S0217590816400014.
33. Sakai, Y., Estudillo, J. P., Fuwa, N., Higuchi, Y., and Sawada, Y. (2017). Do Natural Disasters Affect the Poor Disproportionately? Price Change and Welfare Impact in the Aftermath of Typhoon Milenyo in the Rural Philippines, *World Development*, Vol. 94, 16–26. doi:10.1016/j.worlddev.2016.12.036.
34. Acheampong, A. O. (2018). Economic Growth, CO2 Emissions and Energy Consumption: What Causes What and Where?, *Energy Economics*, Vol. 74, 677–692. doi:10.1016/j.eneco.2018.07.022.
35. Lee, C.-C., Wang, C.-W., Ho, S.-J., and Wu, T.-P. (2021). The Impact of Natural Disaster on Energy Consumption: International Evidence, *Energy Economics*, Vol. 97, 105021. doi:10.1016/j.eneco.2020.105021.
36. Azzarri, C., and Signorelli, S. (2020). Climate and Poverty in Africa South of the Sahara, *World Development*, Vol. 125, 104691. doi:10.1016/j.worlddev.2019.104691.
37. Ogbeide-Osaretin, E. N. (2021). Analysing Energy Consumption and Poverty Reduction Nexus in Nigeria, *International Journal of Sustainable Energy*, Vol. 40, No. 5, 477–493. doi:10.1080/14786451.2020.1815744.
38. Doytch, N., and Klein, Y. L. (2018). The Impact of Natural Disasters on Energy Consumption: An Analysis of Renewable and Nonrenewable Energy Demand in the Residential and Industrial Sectors, *Environmental Progress & Sustainable Energy*, Vol. 37, No. 1, 37–45. doi:10.1002/ep.12640.
39. Idroes, G. M., Hardi, I., Noviandy, T. R., Sasmita, N. R., Hilal, I. S., Kusumo, F., and Idroes, R. (2023). A Deep Dive into Indonesia's CO2 Emissions: The Role of Energy Consumption, Economic Growth and Natural Disasters, *Ekonomikalia Journal of Economics*, Vol. 1, No. 2, 69–81. doi:10.60084/eje.v1i2.115.
40. Nathaniel, S. P. (2021). Ecological Footprint, Energy Use, Trade, and Urbanization Linkage in Indonesia, *GeoJournal*, Vol. 86, No. 5, 2057–2070. doi:10.1007/s10708-020-10175-7.
41. Acaroğlu, H., Kartal, H. M., and García Márquez, F. P. (2023). Testing the Environmental Kuznets Curve Hypothesis in Terms of Ecological Footprint and CO2 Emissions through Energy Diversification for Turkey, *Environmental Science and Pollution Research*, Vol. 30, No. 22, 63289–63304. doi:10.1007/s11356-023-26278-w.
42. Pata, U. K. (2021). Renewable and Non-renewable Energy Consumption, Economic Complexity, CO2 Emissions, and Ecological Footprint in the USA: Testing the EKC Hypothesis with a Structural Break, *Environmental Science and Pollution Research*, Vol. 28, No. 1, 846–861. doi:10.1007/s11356-020-10446-3.
43. Idroes, G. M., Hardi, I., Rahman, M. H., Afjal, M., Noviandy, T. R., and Idroes, R. (2024). The Dynamic Impact of Non-renewable and Renewable Energy on Carbon Dioxide Emissions and Ecological Footprint in Indonesia, *Carbon Research*, Vol. 3, No. 1, 35. doi:10.1007/s44246-024-00117-0.
44. Ehigiamusoe, K. U., Ramakrishnan, S., Lean, H. H., and Mustapha, M. (2023). The Moderating Roles of Renewable and Non-renewable Energy Consumption on the Ecological Impact of Economic Growth in Southeast Asia, *Energy Systems*. doi:10.1007/s12667-023-00616-w.
45. Waheed, R., Chang, D., Sarwar, S., and Chen, W. (2018). Forest, Agriculture, Renewable Energy, and CO2 Emission, *Journal of*

Cleaner Production, Vol. 172, 4231–4238. doi:10.1016/j.jclepro.2017.10.287.

46. Kuldasheva, Z., and Salahodjaev, R. (2023). Renewable Energy and CO2 Emissions: Evidence from Rapidly Urbanizing Countries, *Journal of the Knowledge Economy*, Vol. 14, No. 2, 1077–1090. doi:10.1007/s13132-022-00971-6.

47. Sahoo, B., Behera, D. K., and Rahut, D. (2022). Decarbonization: Examining the Role of Environmental Innovation versus Renewable Energy Use, *Environmental Science and Pollution Research*, Vol. 29, No. 32, 48704–48719. doi:10.1007/s11356-022-18686-1.

48. Liu, C., Niu, H., Hayyat, M., and Hao, V. (2025). Understanding the Relationship between Ecological Footprints and Renewable Energy in BRICS Nations: An Economic Perspective, *International Journal of Hydrogen Energy*, Vol. 118, 46–57. doi:10.1016/j.ijhydene.2025.03.141.

49. Sikdar, A., Bani, N. Y. binti M., Salimullah, A. H. M., Majumder, S. C., Idroes, G. M., and Hardi, I. (2024). Energy Poverty and Environmental Quality Nexus: Empirical Evidence from Selected South Asian Countries, *Ekonomikalia Journal of Economics*, Vol. 2, No. 2, 119–135. doi:10.60084/eje.v2i2.221.

50. Rahman, R. A., White, B., and Ma, C. (2024). The Effect of Growth, Deforestation, Forest Fires, and Volcanoes on Indonesian Regional Air Quality, *Journal of Cleaner Production*, Vol. 457, 142311. doi:10.1016/j.jclepro.2024.142311.

51. Kurniawan, K., Supriatna, J., Sapoheluwakan, J., Soesilo, T. E. B., Mariati, S., and Gunarso, G. (2022). The Analysis of Forest and Land Fire and Carbon and Greenhouse Gas Emissions on the Climate Change in Indonesia, *AgBioForum*, Vol. 24, No. 2, 1–11.

52. Bello, M. O., Solarin, S. A., and Yen, Y. Y. (2018). The Impact of Electricity Consumption on CO2 Emission, Carbon Footprint, Water Footprint and Ecological Footprint: The Role of Hydropower in an Emerging Economy, *Journal of Environmental Management*, Vol. 219, 218–230. doi:10.1016/j.jenvman.2018.04.101.

53. Stef, N., and Ben Jabeur, S. (2020). Climate Change Legislations and Environmental Degradation, *Environmental and Resource Economics*, Vol. 77, No. 4, 839–868. doi:10.1007/s10640-020-00520-2.

54. Tauseef Hassan, S., Xia, E., and Lee, C.-C. (2021). Mitigation Pathways Impact of Climate Change and Improving Sustainable Development: The Roles of Natural Resources, Income, and CO 2 Emission, *Energy & Environment*, Vol. 32, No. 2, 338–363. doi:10.1177/0958305X20932550.

55. Sarkodie, S. A. (2021). Environmental Performance, Biocapacity, Carbon & Ecological Footprint of Nations: Drivers, Trends and Mitigation Options, *Science of The Total Environment*, Vol. 751, 141912. doi:10.1016/j.scitotenv.2020.141912.

56. Galli, A., Iha, K., Moreno Pires, S., Mancini, M. S., Alves, A., Zokai, G., Lin, D., Murthy, A., and Wackernagel, M. (2020). Assessing the Ecological Footprint and Biocapacity of Portuguese Cities: Critical Results for Environmental Awareness and Local Management, *Cities*, Vol. 96, 102442. doi:10.1016/j.cities.2019.102442.

57. Maulidar, P., Fitriyani, F., Sasmita, N. R., Hardi, I., and Idroes, G. M. (2024). Exploring Indonesia's CO2 Emissions: The Impact of Agriculture, Economic Growth, Capital and Labor, *Grimsa Journal of Business and Economics Studies*, Vol. 1, No. 1, 43–55. doi:10.61975/gjbes.v1i1.22.

58. Ansari, M. A. (2022). Re-visiting the Environmental Kuznets Curve for ASEAN: A Comparison between Ecological Footprint and Carbon Dioxide Emissions, *Renewable and Sustainable Energy Reviews*, Vol. 168, 112867. doi:10.1016/j.rser.2022.112867.

59. Erdoğan, S., Yıldırım, D. Ç., and Gedikli, A. (2019). Investigation of Causality Analysis between Economic Growth and CO2 Emissions: The Case of BRICS – T Countries, *International Journal of Energy Economics and Policy*, Vol. 9, No. 6, 430–438. doi:10.32479/ijeep.8546.

60. Chekouri, S. M., Chibi, A., and Benbouziane, M. (2023). The Impact of Natural Resource Abundance on Ecological Footprint: Evidence from Algeria, *Environmental Science and Pollution Research*, Vol. 30, No. 26, 69289–69306. doi:10.1007/s11356-023-26720-z.

61. Aderinto, E. R., and Ogunro, T. T. (2021). Population Growth and Environmental Degradation in Nigeria: A Comparative Analysis of Carbon Dioxide Emissions and Ecological Footprint, *Interdisciplinary Journal of Applied and Basics Subjects*, Vol. 1, No. 4, 26.

62. Our World in Data (OWID). (2024). Natural Disasters, from https://ourworldindata.org/natural-disasters.

63. Our World in Data (OWID). (2024). Fossil Fuels, from https://ourworldindata.org/fossil-fuels.

64. Our World in Data (OWID). (2024). Renewable Energy, from https://ourworldindata.org/renewable-energy.

65. World Bank. (2023). WorldBank Development Indicator Databased, from https://databank.worldbank.org/source/world-development-indicators.

66. Hardi, I., Idroes, G. M., Zulham, T., Suriani, S., and Saputra, J. (2023). Economic Growth, Agriculture, Capital Formation and Greenhouse Gas Emissions in Indonesia: FMOLS, DOLS and CCR Applications, *Ekonomikalia Journal of Economics*, Vol. 1, No. 2, 82–91. doi:10.60084/eje.v1i2.109.

67. Idroes, G. M., Afjal, M., Khan, M., Haseeb, M., Hardi, I., Noviandy, T. R., and Idroes, R. (2024). Exploring the Role of Geothermal Energy Consumption in Achieving Carbon Neutrality and Environmental Sustainability, *Heliyon*, Vol. 10, No. 23, e40709. doi:10.1016/j.heliyon.2024.e40709.

68. Nahrin, R., Rahman, M. H., Majumder, S. C., and Esquivias, M. A. (2023). Economic Growth and Pollution Nexus in Mexico, Colombia, and Venezuela (G-3 Countries): The Role of Renewable Energy in Carbon Dioxide Emissions, *Energies*, Vol. 16, No. 3, 1076. doi:10.3390/en16031076.

69. Baloch, A., Shah, S. Z., Habibullah, M. S., and Rasheed, B. (2021). Towards Connecting Carbon Emissions with Asymmetric Changes in Economic Growth: Evidence from Linear and Nonlinear ARDL Approaches, *Environmental Science and Pollution Research*, Vol. 28, No. 12, 15320–15338. doi:10.1007/s11356-020-11672-5.

70. Suproń, B., and Myszczyszyn, J. (2023). Impact of Renewable and Non-Renewable Energy Consumption and CO2 Emissions on Economic Growth in the Visegrad Countries, *Energies*, Vol. 16, No. 20, 7163. doi:10.3390/en16207163.

71. Arshad, Z., Robaina, M., and Botelho, A. (2020). Renewable and Non-renewable Energy, Economic Growth and Natural Resources Impact on Environmental Quality: Empirical Evidence from South and Southeast Asian Countries with CS-ARDL Modeling, *International Journal of Energy Economics and Policy*, Vol. 10, No. 5, 368–383. doi:10.32479/ijeep.9956.

72. Dickey, D. A., and Fuller, W. A. (1979). Distribution of the Estimators for Autoregressive Time Series with a Unit Root, *Journal of the American Statistical Association*, Vol. 74, No. 366a, 427–431. doi:10.1080/01621459.1979.10482531.

73. Phillips, P. C. B., and Perron, P. (1988). Testing for a Unit Root in Time Series Regression, *Biometrika*, Vol. 75, No. 2, 335. doi:10.2307/2336182.

74. Akaike, H. (1974). A New Look at the Statistical Model Identification, *IEEE Transactions on Automatic Control*, Vol. 19, No. 6, 716–723. doi:10.1109/TAC.1974.1100705.

75. Sasmita, N. R., Phonna, R. A., Fikri, M. K., Khairul, M., Apriliansyah, F., Idroes, G. M., Puspitasari, A., and Saputra, F. E. (2023). Statistical Assessment of Human Development Index Variations and Their Correlates: A Case Study of Aceh Province, Indonesia, *Grimsa Journal of Business and Economics Studies*, Vol. 1, No. 1, 12–24. doi:10.61975/gjbes.v1i1.14.

76. Pesaran, M. H., and Timmermann, A. (2005). Small Sample Properties of Forecasts from Autoregressive Models under Structural Breaks, *Journal of Econometrics*, Vol. 129, No. 1–2, 183–217. doi:10.1016/j.jeconom.2004.09.007.

77. Stock, J. H., and Watson, M. W. (1993). A Simple Estimator of Cointegrating Vectors in Higher Order Integrated Systems, *Econometrica*, Vol. 61, No. 4, 783. doi:10.2307/2951763.

78. Hardi, I., Idroes, G. M., Márquez-Ramos, L., Noviandy, T. R., and Idroes, R. (2025). Inclusive Innovation and Green Growth in Advanced Economies, *Sustainable Futures*, Vol. 9, 100540. doi:10.1016/j.sftr.2025.100540.

79. Hardi, I., Afjal, M., Khan, M., Idroes, G. M., Noviandy, T. R., and Utami, R. T. (2024). Economic Freedom and Growth Dynamics in Indonesia: An Empirical Analysis of Indicators Driving Sustainable Development, *Cogent Economics & Finance*, Vol. 12, No. 1. doi:10.1080/23322039.2024.2433023.

80. Idroes, G. M., Hardi, I., Nasir, M., Gunawan, E., Maulidar, P., and Maulana, A. R. R. (2023). Natural Disasters and Economic Growth in Indonesia, *Ekonomikalia Journal of Economics*, Vol. 1, No. 1, 33–39. doi:10.60084/eje.v1i1.55.

81. Granger, C. W. J. (1969). Investigating Causal Relations by Econometric Models and Cross-spectral Methods, *Econometrica*, Vol. 37, No. 3, 424. doi:10.2307/1912791.

82. Nathaniel, S., and Khan, S. A. R. (2020). The Nexus between Urbanization, Renewable Energy, Trade, and Ecological Footprint in ASEAN Countries, *Journal of Cleaner Production*, Vol. 272, 122709. doi:10.1016/j.jclepro.2020.122709.

83. Idroes, G. M., Rahman, H., Uddin, I., Hardi, I., and Falcone, P. M. (2024). Towards Sustainable Environment in North African Countries: The Role of Military Expenditure, Renewable Energy, Tourism, Manufacture, and Globalization on Environmental Degradation, *Journal of Environmental Management*, Vol. 368, 122077. doi:10.1016/j.jenvman.2024.122077.