

Analysis of Factors Affecting Greenhouse Gas Emissions in Indonesia Using Error Correction Model Approach

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ABSTRACT

Indonesia is committed to substantially reducing greenhouse gas emissions, in line with the 2015 Paris Agreement's long-term goal of holding the global average temperature increase from exceeding 1.5°C above pre-industrial levels. The condition of greenhouse gas emission in Indonesia has an increasing trend with an average growth rate of 6.19% from 2000 to 2023. The amount of greenhouse gas emissions in 2023 reached 1.254 billion tons, with the energy and forestry sectors contributing significantly. This study analyzes whether primary energy consumption, forest area, and gross domestic product value affect reducing greenhouse gas emissions in Indonesia. This study uses the Error Correction Model approach, which is capable of observing greenhouse gas emissions conditions in short-term and long-term models. The best model equation obtained the variable of forest area with greenhouse gas emission, with the analysis showing that optimal forest area has a significant effect on reducing greenhouse gas emissions in the long term. The findings indicate that sustained efforts, reforestation initiatives, and law enforcement on reforestation not only increase the absorption capacity of greenhouse gas emissions by the forest but also align with economic development and environmental sustainability simultaneously in the long term.

Keywords: Error Correction Model, Forest Area, Greenhouse Gas Emissions.

1. INTRODUCTION

The 2015 Paris Agreement is a legally binding international agreement addressing the issue of global climate change. Climate change is defined as changes in temperature and weather patterns that occur over a very long period of time (Ariska et al., 2022). Climate change is caused by normal conditions of Earth's natural variability and human activities that can cause extreme climate change (McCarthy et al., 2002). Given these conditions, the 2015 Paris Agreement seeks to achieve a global average temperature target that does not exceed the 1.5°C threshold (Nations, 2015). An increase in global average temperature that crosses the threshold will trigger the worst-case scenario of climate change, so mitigation efforts are needed to avoid extreme climate change.

The mitigation effort is to reduce substantial greenhouse gas emissions. Temperature increases can be influenced by greenhouse gas emissions, causing climate change conditions (Juliani et al., 2021). The contribution of greenhouse gas emissions to climate change is because greenhouse gases, such as carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O) are trapped in the Earth's atmosphere, causing the Earth's temperature to become warmer (Pratama, 2019). These indications provide a warning of the threat of increasing global average temperatures in the future if no preventive action is taken. Therefore, every country is committed to achieving the Net Zero Emission (NZE) target, including Indonesia.

Indonesia is committed to achieving the NZE target by 2060 as a monumental effort to reduce greenhouse gas emissions. The NZE target is a condition where the amount of carbon released into the atmosphere does not exceed the amount of carbon absorbed by the earth (Zahira & Fadillah, 2022). According to the Ministry of Environment and Forestry, the average trend rate of greenhouse gas emissions in Indonesia from 2000 to 2023 was 6.19% (Menlhk, 2024). The trend rate of greenhouse gas emissions in Indonesia tends to increase every year with the highest record in 2015 at 2,688,464 Gg tons and the lowest record in 2001 at 502,575 Gg tons. The high greenhouse gas emission rate is caused by deforestation activities and peatland fires, so decarbonization efforts are needed to reduce greenhouse gas emissions.

Decarbonization mitigation to achieve the 2060 NZE target can be done through a market-based mechanism, namely emissions trading. Emissions trading is a mechanism to reduce greenhouse gas emissions by trading them. Indonesia, which has one of the largest tropical rainforests in the world, can utilize the potential of emissions trading as a service provider for greenhouse gas emission absorption. The projected revenue from emissions trading in Indonesia is IDR8,000 trillion under the scenario of US\$5 per ton emission credit selling price (Katadata, 2022). Large emissions trading revenues can support mitigation funds and increase the value of Indonesia's gross domestic product, given that climate change can threaten a country's economic stability (Wangke, 2021). Trend data on the value of Indonesia's gross domestic product tends to increase every year with an average growth rate of 10.15% (World Bank, 2023) Based on the Environmental Kuznets Curve (EKC) hypothesis, the country's economic growth can cause environmental degradation, which results in an increase in carbon emissions. Over time, environmental degradation begins to decline due to technological advances, superior human resources, and the use of renewable energy that can reduce greenhouse gas emissions (Febriyanto & Panjawa, 2024). However, mitigating greenhouse gas emissions requires high costs, so economic growth factors play a very important role.

The 2060 NZE target can be achieved gradually by setting an initial target in 2030 to reduce greenhouse gas emissions by 31.89% by own efforts and 41% with international support (Santoso, 2024). Achieving this target must be accompanied by cooperation from various sectors, such as the energy, forestry, and economic sectors, by making low-emission innovation efforts. The energy and forestry sectors contribute the highest greenhouse gas emissions in Indonesia (Menlhk, 2024). According to study, the energy, forestry and economic sectors contribute greatly to the increase in greenhouse gas emissions in Indonesia (Mahira, 2022). Seeing these conditions, efforts need to be made to determine the influence of the energy, forestry, and economic sectors on greenhouse gas emissions in Indonesia. One method that can be used to solve this problem is the Error Correction Model (ECM).

The ECM method is used to see the long-term and short-term effects of a model of independent variables on time series dependent variables (Hendayanti et al., 2017). Time series data has the characteristics of economic volatility and trends which are non-stationarity symptoms. To see the effect on time series data variables, linear regression analysis cannot be used because it can cause a skewed regression relationship pattern. The results of the estimated spurious regression do not describe the true behavior of the time series data, so cointegration analysis is needed to see the long-term relationship between variables by regressing long-term equations where the residual results are stationary at level. However, in time series data there is a phenomenon of inter-temporal (short-term) movement that moves volatile, so the role of

Error Correction Term (ECT) is needed to overcome the imbalance in the short-term trend towards self-adjustment in the long-term trend (Ekananda, 2016).

Previous research for the ECM method on greenhouse gas emissions has been conducted. According to study, the value of gross domestic product has a long-term and short-term influence on increasing carbon emissions because Indonesia has a high economic growth target that encourages a high contribution of pollutant emissions (Rizki & Anggraeni, 2022). Another study stated that energy consumption has a long-term and short-term influence on increasing greenhouse gas emissions due to the massive use of fossil fuels (Amalina et al., 2023). Forest area has a long-term and short-term influence on reducing greenhouse gas emissions due to the ability of forests to absorb emissions (Irfan et al., 2022). Based on previous research studies, this study will analyze the effect of energy consumption, forest area, and gross domestic product on Indonesia's greenhouse gas emissions in the long-term and short-term models using the ECM method, so that it is expected to be a reference for decisions to reduce greenhouse gas emissions in Indonesia to achieve the NZE target in 2060.

From a theoretical perspective, this study is grounded in the EKC framework, which postulates an inverted U-shaped relationship between economic growth and environmental degradation (Grossman & Krueger, 1995). Initially, as gross domestic product increases, environmental quality tends to deteriorate due to industrialization and resource exploitation. However, after surpassing a certain income threshold, economic development fosters environmental improvements through enhanced institutional capacity, technological innovation, and sustainable practices (Almeida et al., 2024). This theoretical lens is essential in understanding how Indonesia's rising gross domestic product, coupled with shifts in energy use and forest conservation, can influence greenhouse gas emission trajectories over time. The EKC framework supports the analysis of whether Indonesia's economic transition aligns with long-term environmental goals under the Paris Agreement and the NZE target in 2060.

2. LITERATURE REVIEW

2.1 Error Correction Model

Error Correction Model (ECM) is a method used to determine the effect of long-term and short-term models of each independent variable on the dependent variable that applied in econometric cases for time series data with non-stationary problems and the presence of deviant regression in the analysis (Hendayanti et al., 2017).

2.2 Greenhouse Gas Emission

Greenhouse gas emission is the release of a set of gases consisting of carbon dioxide (CO_2), methane (CH_4), nitrogen monoxide (NO), nitrogen dioxide (SO_2), and other derived gases that have the potential to inhibit solar radiation reflected by the earth into the atmosphere, causing the earth's surface temperature to warm (Kusumawardhani & Gernowo, 2015). According to the Ministry of Environment and Forestry, the accumulated value of greenhouse gas emissions comes from the activities of the energy, forestry, agriculture, waste management, and IPPU (Industry Process and Production Use).

3. METHODS

The type of research used in this study is quantitative research method with secondary data that has various sources, namely greenhouse gas emissions data from the Ministry of Environment and Forestry, primary energy consumption data from Our World in Data, forest area, and gross domestic product data from World Bank Data. The data sample used totaled 24 data each variable taken from 2000-2023. This study used Error Correction Model that is capable of observing both long-term and short-term models.

The specification of linear regression equation model to obtain the long-term in the Error Correction Model method is as follows (Ekananda, 2016).

$$Y_t = \beta_0 + \beta_1 X_{1,t} + \beta_2 X_{2,t} + \beta_3 X_{3,t} + \mu_t \quad (1)$$

Where Y_t is greenhouse gas emissions in period t , β_0 represents a constant, $\beta_1, \beta_2, \beta_3$ represent variable coefficients with X_1 is primary energy consumption, X_2 is forest area, and X_3 is gross domestic product, and μ_t is cointegration residual.

Then, the specification of linear regression equation model to obtain the short-term in the Error Correction Model method is as follows (Ekananda, 2016).

$$\Delta Y_t = \delta_0 + \delta_1 \Delta X_{1,t} + \delta_2 \Delta X_{2,t} + \delta_3 \Delta X_{3,t} + \gamma ECT_{t-1} + e_t \quad (2)$$

Where Δ denotes differentiation, γ is the speed of adjustment value, and ECT_{t-1} is the value of Error Correction Term which shows the adjustment of the imbalance of the short-run relationship to the long-run.

4. RESULT AND DISCUSSION

4.1 Pre-Processing Data

There are variables with missing values, greenhouse gas emissions in 2023 and forest area in 2022 to 2023, so to complete the data do the approach using the Linear Extrapolation method.

Table 1. Linear Extrapolation Result

Variable	2022	2023
Y	-	1,375,545
X_2	909,221.2	903,165.8

Table 1 shows that the missing value in the greenhouse gas emissions variable in 2023 was 1,375,545 Gg tons (1 Gg = 1,000 tons). Then, the value of the forest area in 2022 and 2023 were 909,221.2 km² and 903,165.8 km². The estimated values were then entered into the research variable dataset.

4.2 Descriptive Statistics

Descriptive statistical analysis using time series plot visualization to determine data trends and correlation coefficients to determine the relationship between research variables.

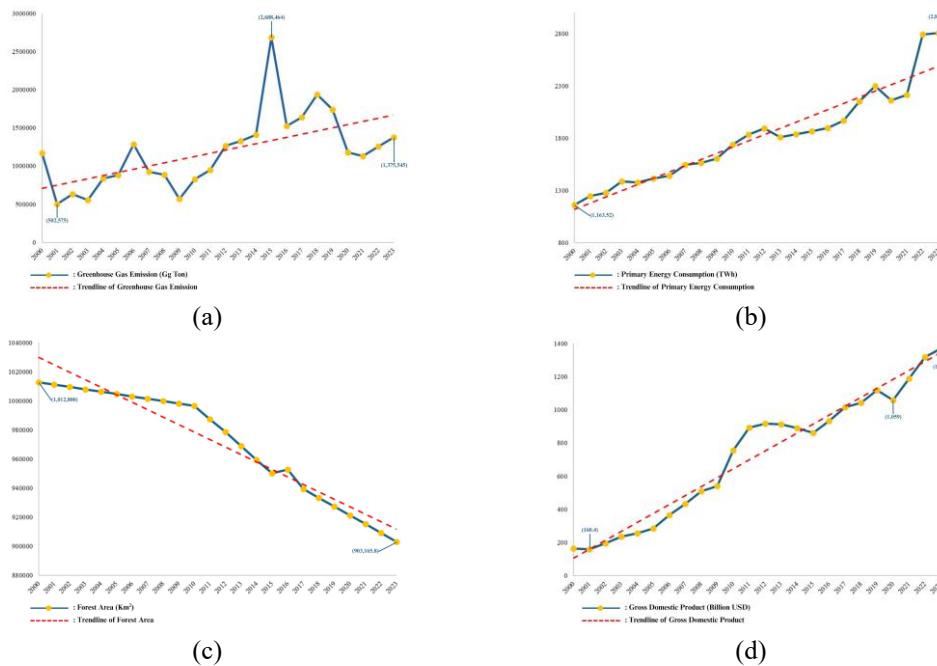


Figure 1. Time Series Plot (a) Greenhouse Gas Emissions, (b) Primary Energy Consumption, (c) Forest Area, (d) Gross Domestic Product

Figure 1(a) illustrates that Indonesia's greenhouse gas emissions data fluctuated from 2000 to 2023, with an average annual growth rate of 6.19%. The trend in the greenhouse gas emissions growth rate shows a tendency to increase each year, peaking in 2015 with a record of 2,688,464 Gg tons. The high greenhouse gas emissions in 2015 were primarily caused by deforestation activities, peatland fires, and the reliance on coal energy to boost the country's electricity supply. By 2023, greenhouse gas emissions had risen to 1,375,545 Gg tons, marking an increase of approximately 9.68% compared to 2022. This rise can be attributed to 2023 being the hottest year, with the global average temperature reaching 1.48°C, higher than the pre-industrial global average temperature of 1850-1900 (Dale, 2024).

Figure 1(b) illustrates that primary energy consumption data in Indonesia has been increasing and fluctuating during certain periods from 2000 to 2023, with an average growth rate of 4.07% each year. The trend in the growth rate of primary energy consumption tends to rise annually, with the highest record of primary energy consumption occurring in 2023 at 2,807.73 TWh. Conversely, the lowest primary energy consumption was recorded in 2000 at 1,163.52 TWh. Indonesia continues to rely on fossil fuels as its main source of energy. According to a report by the Energy Institute, Indonesia is projected to be the country with the highest primary energy consumption in ASEAN by 2023 (Energy Institute, 2024). Therefore, transforming the use of renewable energy is essential to reduce dependence on fossil fuels in the future.

Figure 1(c) illustrates that the forest area data in Indonesia has been decreasing and fluctuating during various periods from 2000 to 2023, with an average growth rate trend of -0.50% per year. The trend in forest area growth rate generally declines each year, with the largest recorded forest area in 2000 at 1,012,800 km². In contrast, the smallest recorded forest area in 2023 was 903,165.8 km². According to a report by the World Resources Institute, by

2023, Indonesia will hold the fourth largest loss of tropical rainforest area globally, following Brazil, the Democratic Republic of Congo, and Bolivia. Therefore, efforts to preserve forest ecosystems by halting deforestation are essential as a measure to mitigate the increase in emissions (Goldman et al., 2025).

Figure 1(d) illustrates that the value of gross domestic product data in Indonesia has been increasing and fluctuating during various periods from 2000 to 2023, with an average growth rate trend of 10.15% per year. The trend in gross domestic product growth rate generally increases every year, with the highest gross domestic product value record in 2023 of USD 1,370 billion. Meanwhile, the record low gross domestic product value in 2001 was 160.4 billion USD. In 2020, the gross domestic product value experienced negative growth of -5.36% due to the Covid-19 pandemic, which paralyzed various sectors.

Table 2. Correlation Coefficient to Greenhouse Gas Emission

	X_1	X_2	X_3
Y	0.482	-0.604	0.571

Table 2 shows that the largest correlation coefficient value is obtained by forest area and greenhouse gas emissions with a value of -0.604. Forest area has a negative relationship with greenhouse gas emissions. This means that if there is an increase in forest area, the value of greenhouse gas emissions in Indonesia will decrease.

4.3 Best Model Selection

The method used is the correlation coefficient and Variance Inflation Factor (VIF) value, with the provision that there is multicollinearity if the correlation coefficient value is greater than 0.7 and the VIF value is greater than 10 (Supriyadi et al., 2017).

Table 3. Correlation Coefficient of Independent Variables

	X_1	X_2	X_3
X_1	1		
X_2	-0.940	1	
X_3	0.953	-0.932	1

Table 3 shows that the correlation coefficient matrix values of the independent variables do not exceed 0.7 or have a strong correlation, so it can be said that there are indications of multicollinearity. Therefore, to form an equation, can use only one of the independent variables so that there is no indication of multicollinearity.

Table 4. VIF Value

Variabl e	VIF
X_1	13.948
X_2	9.763
X_3	12.342

Table 4 shows that the variables of primary energy consumption and gross domestic product value have VIF values of more than 10, so it can be said that there are indications of multicollinearity. Based on the two multicollinearity checks, it can be decided to determine one independent variable by comparing the highest R^2_{Adj} value to get the best model.

The selection of the best model includes a combination of possible regression equations and Principal Component Analysis (PCA), which is one of the methods to handle multicollinearity.

Table 5. Best Model Selection Result

Model	R^2_{Adj}
X_1	19.73 %
X_2	33.53 %
X_3	29.55 %
PCA	28.61 %

Table 5 shows that the independent variable forest area has the highest R^2_{Adj} , which is 33.53%. This is supported by the correlation coefficient value in Table 2 where the forest area and greenhouse gas emissions have the greatest relationship. Therefore, the independent variable used for the ECM model is forest area.

4.4 Error Correction Model Analysis

4.4.1 Identification of Stationary Data

The test method used to see the stationarity of the data in this study is the ADF test with a significant level of $\alpha = 10\%$. If the p-value is less than the significant level, it can be concluded that the data used is stationary.

Table 6. ADF Testing Result

Variabl e	At level		First difference	
	P-value	Result	P-value	Result
$Ln(Y)$	0,280	Non-Stationary	0,000	Stationary
$Ln(X_2)$	0,999	Non-Stationary	0,018	Stationary

Table 6 shows that after first differencing, the p-value of all variables is smaller than the critical value and the p-value is more than 0.1. Therefore, it can be said that all variables have fulfilled the assumption of data stationarity.

4.4.2 Optimum Lag Determination

The criterion used to determine the optimum lag is the Akaike Information Criterion (AIC) value. Determination of the optimum lag is selected if it has the smallest AIC value.

Determination of the optimum lag is used to overcome the problem of autocorrelation between variables.

Table 7. AIC Value Result

Optimum Lag	AIC	Optimum Lag	AIC
0	-3,288	4	-7,158
1	-7,822	5	-7,445
2	-7,711	6	-8,049
3	-7,440	7	-8,522

Table 7 shows the lag that has the smallest AIC value is lag 7 with an AIC value of -8.522 compared to other lags. Thus, the optimum lag used for the classic autocorrelation assumption has lag 7 in the model.

4.4.3 Co-Integration Test

The test method used to determine the Co-Integration relationship is Engle-Granger test with a significant level of $\alpha = 10\%$. If the p-value is less than the significant level, it can be concluded that there is a long-term relationship between variables. The step taken for the Co-Integration test is to form the residual series of the Ordinary Least Square (OLS) equation.

Table 8. Engle-Granger Testing Result

τ	P- value
-4,100	0,0503

Table 8 shows the τ value is smaller than the critical value and the p-value is more than 0.1. Therefore, it can be said that there is a Co-Integration relationship or has a long-run relationship between variables.

4.4.4 Estimation of ECM Parameters

The result of ECM parameter estimation in the long-run and short-run models are as follows.

Long-term model: $Ln(Y_t) = 18,201 - 6,957Ln(X_{2,t})$

Short-term model: $\Delta Ln(Y_t) = -0,140 - 30,795\Delta Ln(X_{2,t}) - 0,589ECT_{t-1}$

The coefficient value of the forest area (FA) variable in the long-term model is $\text{Exp}(-6.957) = 0.00095$, which means that any change in the value of forest area (FA) by one unit in one previous period will affect the current value of greenhouse gas emissions (GHG) by 0.00095 (10^5 Gg Tons). The coefficient value of the forest area (FA) variable in the short-term model is $\text{Exp}(-30.795) = 0.00000$, which means that any change in the value of forest area (FA) by one unit in one previous period will affect the current value of greenhouse gas emissions (GHG) by 0.00000 (10^5 Gg Tons). The ECT coefficient value in the short-term model equation is 0.589 which indicates that the short-term equilibrium fluctuations will be corrected towards the long-term equilibrium with a value of 58.9% where the adjustment process occurs in the first year. Meanwhile, 41.1% of the adjustment process then occurs in the following years.

4.4.5 Analysis of Significance Testing of ECM Model Parameters

The test method used to see the significance of the forest area parameter is the simultaneous test and partial test with a significant level of $\alpha = 10\%$. If the p-value is less than the significant level, it can be concluded that there is significance between variables.

Table 9. Parameter Significance Testing Result

Model	Parameter Significance Testing	
	Simultaneous Test	Partial Test
	P-value	P-value
Long-term	0,005	0,0005
Short-term	0,005	0,044

Table 9 shows that simultaneous significance testing of parameters in the long-term and short-term models has a p-value of less than 0.1. This means that there is at least one parameter that has a long-term influence on greenhouse gas emissions. The results of partial parameter significance testing in the long-term and short-term models have a p-value of less than 0.1. This means that the forest area variable has a significant effect on greenhouse gas emissions.

4.4.6 Analysis of Classical Assumptions Testing

The classical assumption testing methods used are the Jarque-Bera Normality test, Lagrange Multiplier Autocorrelation test, and Breusch-Pagan Heteroscedasticity test with a significant level of $\alpha = 10\%$. If the p-value is less than the significant level, then the classical assumptions are met.

Table 10. Classical Assumptions Testing Result

Model	Normality	Autocorrelation	Heteroscedasticity
	P-value	P-value	P-value
Long-term	0,824	0,392	0,826
Short-term	0,934	0,397	0,771

Table 10 shows that in the long-term and short-term models, the p-values in the Normality test, Autocorrelation test, and Heteroscedasticity test have values less than 0.1. Therefore, it can be said that the classical assumptions have been met, so the ECM model formed is good.

4.5 The Impact of Forest Area

The parameter signs on the coefficient value of the forest area variable shows a negative relationship. This means that if there is an increase in forest area in Indonesia, the amount of greenhouse gas emissions will decrease. The result of the analysis is directly proportional to the existing conditions or theories. Forest is one of the sources of the greenhouse gas emissions absorption. Indonesia as one of the countries with the largest tropical rainforest area of 125.9 million hectares has the potential to absorb carbon emissions of 25.18 billion tons. Indonesia can utilize its forest potential as a carbon trading activity. With a carbon trading price scenario of US\$5 per tons in the carbon market, Indonesia is projected to earn IDR8,000 trillion with

the high potential of carbon trading, the revenue can be utilized to create low-emission technologies and policies.

From the parameter estimation results, the forest area variable shows a very small effect on the greenhouse gas emission variable. This shows that forests do not play a significant role in reducing greenhouse gas emissions. This result is proven by recent research which states that trees and green land can hardly absorb carbon emissions by 2023. This condition is very worrying because it can slow down the rate of carbon sequestration. The failure to absorb carbon emissions is caused by human activities, such as deforestation, fossil fuel use, and land expansion, which cause global average temperature changes to increase by 2023. High temperatures will disrupt the photosynthesis process of trees or plants, so that the absorption of carbon emissions is not optimal (Greenfield, 2024). Therefore, efforts are needed to maintain the role of forests as carbon emission sinks by reforestation, reducing land expansion, and maintaining climate change, so that in the future forests can play an optimal role in reducing greenhouse gas emissions in an effort to achieve Indonesia's Net Zero Emission target in 2060.

5. CONCLUSION

Forest area has a negative influence on greenhouse gas emissions. It can be said that, if there is an increase in forest area, greenhouse gas emissions will decrease. However, the decline in greenhouse gas emissions will be optimal in the long term by 0.00095 Gg tons per one km². This is because the role of forests as a medium for absorption of greenhouse gas emissions is weakening due to an increase in global average temperature, so climate change mitigation efforts and deforestation efforts are needed in forests.

Moreover, the findings highlight the importance of integrating forest expansion strategies with broader climate policy frameworks. Forest-based carbon sequestration must be complemented by sustainable land use practices, reforestation initiatives, and legal enforcement against deforestation. Additionally, aligning national mitigation strategies with international mechanisms—such as REDD+ (Reducing Emissions from Deforestation and Forest Degradation)—can strengthen institutional capacity and financial support. These measures not only enhance the long-term absorption capacity of forests but also ensure that economic development and environmental sustainability proceed in tandem, in line with the Environmental Kuznets Curve hypothesis and Indonesia's 2060 Net Zero Emission commitment.

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