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Indonesia's Greenhouse Gas Puzzle: VECM Unravels Impact

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ABSTRACT

This study investigates the dynamic relationship between greenhouse gas (GHG) emissions, agricultural activity, forest area, and other industrial sectors in Indonesia using the Vector Error Correction Model (VECM) approach. The analysis employs annual data from 1990 to 2023 to capture both short-run adjustments and long-run equilibrium among the variables. The results indicate that in the short run, agricultural and industrial activities significantly increase GHG emissions, while changes in forest area have a negative but statistically insignificant effect. The negative and significant error correction term confirms the existence of long-run equilibrium, with approximately 30% of deviations from equilibrium corrected each period, indicating moderate adjustment speed. In the long run, agricultural and industrial sectors remain key contributors to emission growth, whereas forest expansion mitigates emissions over time. Diagnostic and stability tests confirm that the model is statistically sound, stable, and free from serial correlation and heteroskedasticity. The impulse response analysis further reveals that shocks from agriculture and industry lead to persistent increases in emissions, while forest shocks exert stabilizing effects. The findings underscore the need for integrated and sustainable policy interventions across sectors. Policymakers should promote climate-smart agricultural practices, enhance industrial energy efficiency, and strengthen forest conservation efforts to achieve balanced economic and environmental outcomes. Moreover, coordinated cross-sectoral policies and investments in green technology are crucial to ensure Indonesia's transition toward a low-carbon and sustainable growth path.

Keywords: Greenhouse Gas Emissions, Agriculture Land, Forest Land, Indonesia, VECM
JEL Classifications: Q54, Q15, Q23, O13, C32

1. INTRODUCTION

Unavoidable climate change makes adaptation a necessity. Various compilations of meteorological data show an increasing climate variability, with previously unprecedented extreme weather conditions. The heightened occurrence of these extreme events is linked to the phenomenon of global warming (Meehl et al., 2000). This rapidly advancing phenomenon is feared to impact the rising frequency of hydrometeorological disasters and the depletion of natural resources, especially on the Earth's surface. Consequently, this phenomenon is expected to impede development or even threaten the outcomes of development. On the other hand, global warming will persist due to the inertia of the climate system, even if greenhouse gas emissions were halted immediately. One of the causes of global climate change is the increasing of greenhouse gas (GHG) emissions resulting from various activities that raise the Earth's temperature. The consequences of global climate change also affect the balance of ecosystems for living organisms.

The impacts of climate change include rising sea levels, altered rainfall patterns, decreased land area and crop productivity, reduced quantity and quality of water, species extinction, and habitat destruction. These climate-induced impacts pose challenges to both social and economic sustainable development and hinder the achievement of development goals. The dynamics of land use change have the potential to increase carbon emissions, with approximately 85% of emissions in Indonesia in 2015 originating from land use activities (Krisnawati et al., 2015).

The primary contributor to greenhouse gases is carbon. Green spaces in forest ecosystems absorb GHG by transforming carbon dioxide (CO_2) into carbon (C) within trees, understory plants, and soil. Forests absorb CO_2 from the air through photosynthesis and store it as forest biomass. Forest biomass contains about 80% of terrestrial carbon above ground and approximately 40% below ground. Land conversion, deforestation, forest degradation, and reforestation can alter land cover types, resulting in changes in the composition of terrestrial biomass (Agus et al., 2013).

According to Smith et al. (2014), agriculture, forestry, and other land uses stand as the second-largest contributor to greenhouse gas (GHG) emissions, accounting for 20-24% of the total emissions, with a more significant impact in developing countries. Based on the World Resources Institute (WRI), agricultural emissions comprise 11.8% of the total global GHG emissions. It is projected that by 2050, global agricultural GHG emissions could increase by up to 58% (World Resources Institute, 2019).

In line with Mannina et al. (2017) and FAO (2012), greenhouse gas (GHG) emissions originating from agricultural activities primarily stem from deforestation, livestock rearing, soil management, and the use of agricultural machinery powered by fossil fuels. This is further emphasized by Agboola and Bekun (2019) and Shabbir et al. (2021). The significant role played by agricultural practices in GHG emissions is due to their heavy reliance on energy sourced from fossil fuels. Agriculture also affects the land's capacity to absorb light and heat, potentially leading to radiative forcing (Blanco et al., 2014). Additionally, land degradation and deforestation caused by human-induced land use activities can impose stress on the land, resulting in anthropogenic emissions. Regarding forestry, the Global Forest Resources Assessment (2010) indicates that the reduction in forested areas and the exploitation of trees for products or fossil fuels lead to the release of approximately one billion tons of carbon annually into the atmosphere.

Moreover, other land comprises desolate terrains and uncultivated agricultural territories, determined by subtracting the combined area of forests, grasslands, settlements, and cultivated lands from the total area (Jenkins et al., 2006). Frequently devoid of management, predicting changes in carbon reserves, non-CO_2 emissions, and sequestrations in such regions poses a significant challenge. Transformation of land into "alternative territory" can occur, for instance, as a result of deforestation causing profound degradation, the release of carbon reserves, and the subsequent emissions.

According to Climate Watch data (2020), Indonesia produced approximately 1.48 billion tons/gigatons of carbon dioxide equivalent (Gt CO_2e) GHG emissions in 2020. This amount represents 3.1% of global greenhouse gas emissions, totaling 47.5 Gt CO_2e. Despite its relatively small percentage, Indonesia's GHG emissions in 2020 ranked as the sixth-largest globally, following China, the United States, India, the European Union, and Russia. Breaking down the sources, in 2020, the majority of Indonesia's national GHG emissions originated from the energy sector (44%), followed by land use/forestry (34%), agriculture (10%), waste (9.4%), and industrial processes (2.3%). On a global scale, GHG emissions from the energy sector are significantly more dominant (75%) compared to the agricultural sector (12%), industrial processes (6.6%), waste (3.5%), and land use/forestry (2.9%). Regarding sector-specific contributions on a global scale, Indonesia's most significant contribution to GHG emissions comes from land use/forestry, accounting for 35.9%.

As discussed earlier, energy consumption is recognized as the most prevalent cause of environmental pollution, and numerous prior studies have explored various facets of energy use and its impact on the environment. However, this research contributes to the literature in several ways. Initially, agriculture, forestry, and other land uses play a substantial role in global GHG emissions, yet there is a limited body of research examining their environmental impact. Agriculture, forestry, and other land uses constitute a unique sector in this context, as their mitigation potential stems from both increased GHG sequestration and emission reduction through land and livestock management (Smith et al., 2014). Moreover, unlike previous literature, this study employs the VECM approach to investigate not only the short-term but also the long-term behavior of the three land use categories contributing to GHG emissions. This approach will enhance our understanding of how different land use types contribute to the majority of GHG emissions. Lastly, this study presents evidence concerning diverse land uses in Indonesia, one of the largest global emitters of GHGs. In Indonesia, where activities related to agriculture, forestry, and other land uses constitute a significant portion of the national economy, they pose potential challenges that could be detrimental to the ecosystem. Research often emphasizes short-term effects, but there is a gap in understanding the long-term consequences and feedback mechanisms associated with land use changes on greenhouse gas emissions, including the impact on ecosystem resilience and adaptability.

2. LITERATURE REVIEW

Greenhouse gas (GHG) emissions originating from agricultural activities, forestry practices, and other land use endeavors have garnered substantial attention in research circles due to their noteworthy contribution to the overall global emissions. Research efforts over the last 20 years have delved deeply into environmental concerns, attracting the interest of contemporary scholars who have meticulously scrutinized this particular phenomenon. Analysis of existing literature reveals a close interconnection between the forestry sector and the economy; the advancement of any economy often comes at the cost of prolonged forest depletion. The reduction in global forest coverage can be attributed to population expansion, primarily fueled by the escalating demand for essential resources such as food, fiber, fuel, and other natural commodities, ultimately resulting in a heightened rate of forest cover depletion. Various studies have shown that deforestation has a significant impact on carbon emissions (Baccini et al., 2012; Damette and Delacote, 2012; FAO, 2020).

The depletion of forested lands on a global scale emerges as a key factor contributing to global warming, climate change, soil erosion, and biodiversity loss, consequently leading to a surge in CO_2 emissions ranging from 6% to 17%. The conversion of tropical forests into pastures has been observed to escalate emissions to varying extents over a span of two decades, although subsequent emissions might exhibit a decline compared to those emanating from undisturbed forests. Studies by Foley et al. (2005) emphasize that since 1850, around 35% of human-induced CO_2 emissions can be directly linked to alterations in land use practices. Regarding agricultural practices, Qiao et al. (2019) undertook a comprehensive evaluation of the environmental impacts of agriculture within G20 nations, employing the Environmental Kuznets Curve (EKC) framework spanning from 1990 to 2014. The relationship between the agricultural sector and greenhouse gas emissions has been discussed in several studies (Chen et al., 2008; Veldkamp and Keller, 1997; Waheed et al., 2018). Their primary conclusions affirmed the presence of the EKC phenomenon within developed economies. Similarly, Zafeiriou and Azam (2017) conducted a study across France, Spain, and Portugal, exploring the correlation between the net value-added index per capita, agricultural value added, and CO_2 emissions. They confirmed the short-term manifestation of the EKC across all surveyed countries, while in the long run, only France and Spain demonstrated the discernible EKC trend.

In another study, Koondhar et al. (2021) analyzed the asymmetric causation relationship among agricultural carbon emissions, energy consumption, fertilizer utilization, and cereal food production in Pakistan. The results of the linear Granger causality analysis confirmed the causal relationship between energy consumption and fertilizer application on cereal food production. Nonlinear Granger causality examination showed that cereal food production had a causal impact on agricultural carbon emissions and energy consumption. Another study exploring the long-term relationship between agriculture and CO_2 was conducted by Gokmenoglu et al. (2019) for the period 1971-2014 in China. This research investigated the long-term relationship between agriculture and CO_2 using an autoregressive distributed lag (ARDL) approach. The ARDL estimation outcomes clarified that agricultural progress positively and rigidly impacts CO_2 emissions. Various other studies have also supported the relationship between income and economic progress in China conducted by Cole et al. (1997) and Janzen (2004). Moreover, Aziz et al. (2020) found that the forestry, agricultural, and renewable energy sectors play a significant role in testing the Environmental Kuznets Curve in Pakistan.

Similarly, several studies have focused on greenhouse gas (GHG) emissions and have investigated the agricultural influence on such emissions. The groundbreaking study by Cole et al. (1997) examined the environmental impact of agricultural practices using GHG as an environmental proxy, revealing that substantial quantities of GHG are released into the environment due to agricultural operations. Furthermore, Janzen (2004) and Smith (2004) explored the same phenomenon, examining carbon sequestration in connection to agricultural practices. They proposed that burning of plant debris and release of organic matter from soil lead to contamination.

In a study conducted by Kehagias et al. (2015), it was shown that the traditional use of fossil fuels significantly contributes to GHG emissions by 46.4%, while fertilizers contribute by 20.9%. Furthermore, Han et al. (2018) investigated the emissions of CH_4 and N_2O from agriculture, revealing that major economies exhibit higher emission levels per individual. Research conducted by Zhou et al. (2007) estimated CH_4 and N_2O emissions from poultry and livestock. Huang and He (2012) investigated the impact of fertilizer application, agricultural machinery, and variations in energy consumption on GHG emissions using data from 31 provinces in China from 1995 to 2007. They utilized a spatial error model and illustrated that excessive use of pesticides and fertilizers, combined with investment in conventional machinery operations, are the primary factors contributing to pollution in China.

Upon examination of the literature in the field of forestry, prior research has been dedicated to exploring the validity of the Environmental Kuznets Curve (EKC) hypothesis in relation to forest resources as discussed by Foster and Rosenzweig (2002). Recent findings by Zambrano-Monserrate et al. (2018) have unveiled a prolonged correlation between deforestation and economic advancement across five European nations. The research conducted by Zhang et al. (2004) has determined that China exhibits confirmation of a forest-induced EKC during the later phases, drawing from analyses of regional, provincial, and national models of China's forested regions spanning from 1999 to 2010. Examining data from the years 2002 to 2015 in China, Hao et al. (2019) investigated the same connection, illustrating that the production of timber and expansion of afforestation areas predominantly escalate alongside economic progress, subsequently declining upon reaching a specific threshold. Additionally, Van Der Werf et al. (2010) have disclosed that activities such as forest fires and decay contribute to emissions, portraying a positive correlation between forest and other land uses. In a separate study by Basyuni et al. (2018) regarding various land categories, it was revealed that the degradation of barren and shrub land serves as a significant factor in carbon emissions, with shrub land alone contributing 30.6% to the overall CO_2 emissions in Indonesia.

Upon scrutiny of the prevailing body of literature, a notable insufficiency is evident in the realm of studies examining the interplay between greenhouse gas (GHG) emissions and the sectors of agriculture and forestry. Nevertheless, scant research delves into the repercussions of alternative land utilizations on environmental emissions. It is discernible that alterations in land coverage, including the depletion of forests and natural freshwater reservoirs, have the potential to induce land deterioration, consequently instigating environmental harm and ecosystemic disruption on a global scale. Furthermore, a pivotal global phenomenon is the escalating population growth, which engenders significant demands for agricultural commodities. The process of urbanization, in reciprocation, is accompanied by the phenomena of excessive resource consumption, land fragmentation, and the loss of biodiversity as documented by Huang et al. (2020) and Ridzuan et al. (2020).

Indonesia's Climate Change Data (2020) also indicates a rising trend of emissions originating from several key sectors, highlighting the urgency of understanding the environmental impacts of land use changes within the Indonesian context. Based on literature studies, it can be concluded that many studies focus on individual components (agriculture, forestry, or other land uses), but there is a need for comprehensive, integrated assessments that consider the synergies and trade-offs between these land uses and their cumulative impact on GHG emissions. Research often emphasizes short-term effects, but there is a gap in understanding the long-term consequences and feedback mechanisms associated with land use changes on GHG emissions, including the impact on ecosystem resilience and adaptability. Therefore, this study aims to examine the effects of agricultural land, forestry land, and other land uses on the composite indicator of environmental degradation, specifically GHG emissions. A comprehensive understanding of GHG emissions across all sectors is crucial for identifying alternatives to reduce emissions.

3. METHODS

This research aims to investigate the causal effect of agricultural land, forestry, and other land on greenhouse gas emissions in Indonesia. To achieve this objective, the analysis involves variables such as agricultural land, forest land, and other land. Other land is defined as land not categorized as agricultural or forest land, encompassing barren and built-up land. Data are collected from the World Development Indicators (WDI). The link to statistical data in this research is https://databank.worldbank.org/. Variables for greenhouse gas (GHG) emissions are measured in kilotons of CO_2 equivalent (kt CO_2 eq), agricultural land is measured in square kilometers (km²), forest land is measured in square kilometers (km²), and other land is measured in hectares (ha). This study uses data from 1990 to 2023. Operational definitions of all variables used in this study, including greenhouse gas emissions, agricultural land, forest land, other land, and total land area, are presented in Table 1.

The analysis employs a restricted vector autoregressive (VAR) model to examine the causality between variables. This model is built upon a vector error correction model (VECM), which is a multiple equation model derived from the restricted VAR. Integrated VAR-VECM Framework can evaluate the potential benefits and drawbacks of an integrated framework that combines VAR and VECM approaches and investigate how such a framework can capture both short-term dynamics and long-term equilibrium relationships in the context of greenhouse gas emissions from agriculture, forestry, and other land use. Furthermore, through VAR or VECM can explore the dynamic interactions and feedback mechanisms between agriculture, forestry, and other land use on greenhouse gas emissions and investigate how changes in one sector may influence the emissions in other sectors over time, and whether these relationships are better captured through VAR or VECM.

In this study, an error correction model is utilized due to the increased efficiency of coefficient estimates obtained from the VAR resulting in VECM representation. Additionally, all variables are treated as endogenous for tests related to long-run parameters (Hajifar et al., 2021; Jang and Ogaki, 2004). With GHG as the primary variable of interest, the VECM equations are constructed based on the restrictions of Wald test coefficients, where Equation 1 estimates the long-run causality between variables, and Equation 2 estimates short-run causal effects, as illustrated below:

$$ECT_{t-1} = \delta_i\, emissions_{t-1} - \delta_j\, agriculture_{t-j} - \delta_m\, forest_{t-m} - \delta_n\, other_{t-n}$$

$$\begin{aligned}\Delta emissions_t &= \delta_1 + \sum_{i=1}^{k-1} \delta_i \Delta emissions_{t-i} \\ &+ \sum_{j=1}^{k-1} \delta_j \Delta agriculture_{t-j} + \sum_{m=1}^{k-1} \delta_m \Delta forest_{t-m} \\ &+ \sum_{n=1}^{k-1} \delta_n \Delta other_{t-n} + \lambda_1 ECT_{t-1} + \varepsilon_{1t}\end{aligned}$$

$$\begin{aligned}\Delta agriculture_t &= \delta_2 + \sum_{i=1}^{k-1} \delta_i \Delta emissions_{t-i} \\ &+ \sum_{j=1}^{k-1} \delta_j \Delta agriculture_{t-j} + \sum_{m=1}^{k-1} \delta_m \Delta forest_{t-m} \\ &+ \sum_{n=1}^{k-1} \delta_n \Delta other_{t-n} + \lambda_2 ECT_{t-1} + \varepsilon_{2t}\end{aligned}$$

$$\begin{aligned}\Delta forest_t &= \delta_3 + \sum_{i=1}^{k-1} \delta_i \Delta emissions_{t-i} \\ &+ \sum_{j=1}^{k-1} \delta_j \Delta agriculture_{t-j} + \sum_{m=1}^{k-1} \delta_m \Delta forest_{t-m} \\ &+ \sum_{n=1}^{k-1} \delta_n \Delta other_{t-n} + \lambda_3 ECT_{t-1} + \varepsilon_{3t}\end{aligned}$$

$$\begin{aligned}\Delta other_t &= \delta_4 + \sum_{i=1}^{k-1} \delta_i \Delta emissions_{t-i} \\ &+ \sum_{j=1}^{k-1} \delta_j \Delta agriculture_{t-j} + \sum_{m=1}^{k-1} \delta_m \Delta forest_{t-m} \\ &+ \sum_{n=1}^{k-1} \delta_n \Delta other_{t-n} + \lambda_4 ECT_{t-1} + \varepsilon_{4t}\end{aligned}$$

Notes:
"k-1 is the lag length is reduced by 1. δ_i, δ_j, δ_m, δ_n are short-run dynamic coefficient of the model's adjustment long-run equilibrium relationships. λ_i is speed of adjustment parameter with negative sign. ECT_{t-1} represents the error correction term is the lagged value of the residuals obtained from the cointegrating regression of the dependent variable on the regressors. Contains long-run information derived from the long-run cointegrating relationship, and ε_{1t} is the error term".

Here is the explanation of each variable:

"According to definition provided by World Bank, CO_2 emissions (kt) are those stemming from the burning of fossil fuels and the manufacture of cement. They include carbon dioxide produced during consumption of solid, liquid, and gas fuels and gas flaring" (World Bank, 2024).

"According to definition provided by World Bank, agricultural land (sq. km) is Agricultural land refers to the share of land area that is arable, under permanent crops, and under permanent pastures. Arable land includes land defined by the FAO as land under temporary crops (double-cropped areas are counted once), temporary meadows for mowing or for pasture, land under market or kitchen gardens, and land temporarily fallow. Land abandoned as a result of shifting cultivation is excluded. Land under permanent crops is land cultivated with crops that occupy the land for long periods and need not be replanted after each harvest, such as cocoa, coffee, and rubber. This category includes land under flowering shrubs, fruit trees, nut trees, and vines, but excludes land under trees grown for wood or

Table 1: Operational research variables

No	Variable	Operational definition	Unit/Data form	Data source (WDI Code/ Database)	Expected relationship to GHG
1	Greenhouse Gas Emissions (GHG)	Total greenhouse gas emissions generated by all sectors, including Land Use, Land-Use Change, and Forestry (LULUCF).	Megaton CO_2 equivalent (Mt CO_2e)	CAIT–Climate Watch or World Development Indicators (derived from EN.ATM.GHGT.KT.CE)	(Dependent variable)
2	Agricultural Land (AL)	Land area used for agricultural activities, including cropland, pastures, and plantations.	Square kilometers (sq. km)	WDI: AG.LND.AGRI.K2	Positive (+) expansion of agricultural land tends to increase GHG emissions through deforestation and fertilizer use.
3	Forest Land (FL)	The area of land covered by natural or planted forests that act as carbon sinks.	Square kilometers (sq. km)	WDI: AG.LND.FRST.K2	Negative (−) an increase in forest area reduces GHG emissions due to carbon absorption capacity.
4	Other Land (OL)	Land not classified as agricultural or forest land, such as settlements, built-up areas, and shrublands. Calculated as: Total Land Area (Agricultural Land+Forest Land).	Square kilometers (sq. km)	Author's calculation based on WDI: AG.LND.TOTL. K2 − (AG.LND.AGRI. K2+AG.LND.FRST.K2)	Positive (+) urbanization and land development increase emissions from economic and transport activities.
5	Total Land Area (TL)	The total area of land in a country, encompassing all types of land use.	Square kilometers (sq. km)	WDI: AG.LND.TOTL.K2	(Control/used for derived calculation)

timber. Permanent pasture is land used for five or more years for forage, including natural and cultivated crops" (World Bank, 2024).

"According to definition provided by World Bank, Forest area (sq. km) is land under natural or planted stands of trees of at least 5 meters in situ, whether productive or not, and excludes tree stands in agricultural production systems (for example, in fruit plantations and agroforestry systems) and trees in urban parks and gardens" (World Bank, 2024).

"According to definition provided by World Bank, land area (sq. km) is a country's total area, excluding area under inland water bodies, national claims to continental shelf, and exclusive economic zones. In most cases the definition of inland water bodies includes major rivers and lakes" (World Bank, 2024).

Bella (2018) and Katircioglu et al. (2014) have emphasized, the dependent variables in equations (1) to (3) may exhibit delayed adjustments to their equilibrium levels over an extended period. As a result, an examination was conducted to evaluate the rate of adjustment between short-run and long-run levels of emissions, agriculture, forest, and other factors by employing dynamic Vector Error Correction Model (VECM) frameworks. To begin with, four Vector Autoregression (VAR) models were constructed with a lag parameter of p. Within the VAR framework, each endogenous variable within the system is modeled as a function of its lagged values across all endogenous variables. Given the multitude of coefficients present in each equation of the VAR model, the primary focus lies not on these coefficients but on the utilization of impulse response functions and Granger causality tests for analytical purposes.

4. RESULTS AND DISCUSSION

4.1. Descriptive Statistics

Table 2 presents the descriptive statistics of the variables used in this study. The variables include total greenhouse gas (GHG) emissions, agricultural activity, forest area, and other contributing factors.

Table 2: Descriptive statistics

Variable	Mean	Standard Deviation	Min	Max
Emissions	1233.18	545.8733	539.3634	2472.894
Agriculture	529577.7	80200.52	413510	661152
Forest	1010641	76374.92	889667.4	1185450
Other	319230.2	43235.61	175290	392949

Source: Data Processed, 2025

The mean value of emissions is approximately 1,233.18 Mt CO_2e, indicating the average level of GHG emissions produced over the study period. The standard deviation of 545.87 reflects substantial variation in annual emissions, suggesting that Indonesia's emission levels have fluctuated considerably due to changing economic activities, land use patterns, and environmental policies. The minimum emission value (539.36 Mt CO_2e) and maximum (2,472.89 Mt CO_2e) confirm the presence of significant dynamics over time.

The agriculture variable shows an average value of 529,577.7, with a relatively large dispersion (standard deviation of 80,200.52). This variation suggests that agricultural expansion and productivity levels have changed notably, likely reflecting shifts in land utilization, policy support, and technological adoption within the sector.

For the forest variable, the mean value of 1,010,641 and standard deviation of 76,374.92 indicate a gradual decline in forest area over time. The minimum and maximum values (889,667.4 and 1,185,450, respectively) show that deforestation and land conversion have played an important role in influencing Indonesia's carbon balance and emission trends.

Lastly, the other category, which includes additional land-use components and miscellaneous sources of emissions, has an average value of 319,230.2 with a standard deviation of 43,235.61. The moderate variability of this variable implies that these components have remained relatively stable compared to the other major sectors.

Overall, the descriptive statistics suggest that variations in GHG emissions are closely associated with dynamics in the agricultural and forestry sectors. The wide dispersion across variables indicates that structural shifts in land use and production intensity are key factors driving Indonesia's emission patterns. These findings provide a preliminary understanding of how sectoral changes contribute to the country's overall GHG emissions before conducting more detailed econometric analysis.

4.2. Unit Root Test

The importance of unit root testing in this study lies in its ability to determine the presence of unit roots among variables, enabling the consideration of panel data as stationary if no unit roots are detected. Ultimately, the validity of the relationship between independent and dependent variables can be confirmed. The unit root testing in this study also relies on statistical tests at a certain significance level and first difference tests. The results of the unit root tests can be found in Table 3.

The Augmented Dickey-Fuller (ADF) test was conducted to examine the stationarity of each variable in the model. A variable is considered stationary when the absolute value of the ADF statistic is greater than the critical value at the 5% significance level, indicating that it does not contain a unit root.

As shown in Table 3, the ADF statistics for all variables at the level form are generally not significant, implying that the series are non-stationary in their original form. However, after taking the first difference, all variables show a substantial increase in the ADF statistic values, exceeding the critical value at the 5% significance level. This result suggests that the variables emissions, agriculture, forest, and other land use become stationary after first differencing.

Therefore, it can be concluded that each variable is integrated of order one, I(1). This finding indicates that the variables share similar stochastic trends over time, making them suitable for further analysis using cointegration or time-series models such as the Vector Error Correction Model (VECM) or trend regression models that capture both short-term and long-term relationships among variables.

Table 3: Unit root tests (Augmented Dickey-Fuller)

Variable	Unit root tests	
	At level	At first difference
Emissions	−1.875	−8.093
Agriculture	0.816	−6.227
Forest	−3.611	−2.273
Other	−4.371	−5.454

Source: Data Processed, 2025. Significance level at α=5%

Table 4: Selection criteria for optimal lags

Lag	LL	LR	FPE	AIC	HQIC	SBIC
0	−1253.75		3.1e+31	83.8499	83.9096	84.0367
1	−1122.31	262.87	1.4e+28	76.1541	76.4529*	77.0882*
2	−1104.01	36.599*	1.3e+28*	76.0008*	76.5387	77.6823
3	−1095.22	17.592	2.5e+28	76.4811	77.2581	78.9098
4	−1083.9	22.625	4.8e+28	76.7936	77.8096	79.9696

At 5% level, * indicates the lag order selection criterion. Source: Data Processed, 2025

4.3. Optimal Lag Criteria

Optimal Lag Criteria is a criterion used in time series analysis to select the optimal lag (delay time) in autoregressive models or vector autoregressive models (VAR). Optimal lag selection is crucial as it can influence the results of the analysis and predictions of the model. The results of the optimal lag criteria testing can be found in Table 4.

From the results, the LR, FPE, and AIC criteria all indicate that the optimal lag is 2, as shown by the smallest values and the presence of an asterisk (*) at lag 2. Meanwhile, the HQIC and SBIC criteria suggest that the optimal lag is 1.

In practice, the final decision on the optimal lag is typically based on the majority rule or the criteria that best suit the model's purpose. Given that most of the selection criteria (LR, FPE, and AIC) point to lag 2, this lag length is chosen as the optimal lag for subsequent analysis.

Selecting the correct lag length is crucial because it ensures that the dynamic relationships among variables are captured accurately while avoiding problems of overfitting or loss of degrees of freedom. Therefore, based on these results, a lag order of two (lag = 2) provides the most efficient and reliable specification for further modeling, such as cointegration testing and Vector Error Correction Model (VECM) estimation.

4.4. Stability Test

After selecting the optimal lag, which is lag 4, the stability test is conducted next. The results of the stability test are presented in the Table 5.

The stability test is performed to ensure that the estimated Vector Error Correction Model (VECM) or Vector Autoregressive (VAR) model satisfies the stability condition, which is a prerequisite for the validity of the model's dynamic analysis. Stability is assessed based on the modulus of the eigenvalues of the companion matrix.

A model is considered stable (or dynamically stationary) when all eigenvalues lie inside the unit circle, meaning that all modulus values are <1 ($|\lambda| < 1$). This condition ensures that the system converges to its long-run equilibrium and that the impulse response functions and variance decompositions are reliable for interpretation.

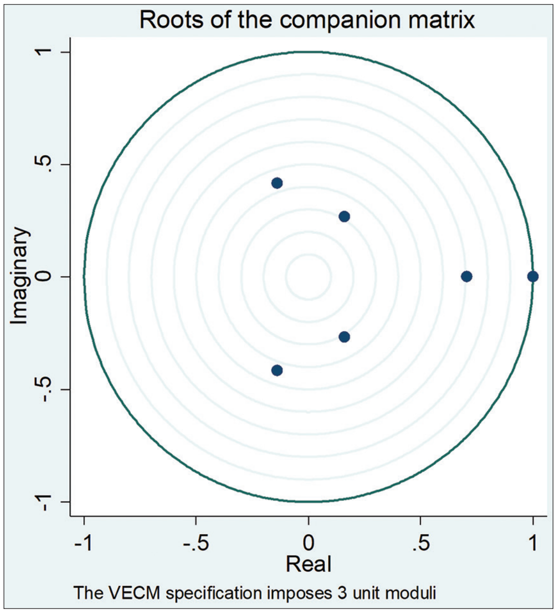
As presented in Table 5, all modulus values are below 1, with the largest modulus recorded at 0.708197. This indicates that the model fulfills the stability condition. Therefore, the estimated

Table 5: Stability test

Eigenvalue	Modulus
0.708197	0.708197
−0.708197	0.708197
−0.4421294	0.442129
0.4421294	0.442129
−0.0751884+0.3818831i	0.389215
−0.0751884−0.3818831i	0.389215
0.0751884+0.3818831i	0.389215
0.0751884−0.3818831i	0.389215

Source: Data Processed, 2025

Figure 1: Roots of the companion matrix



VAR/VECM model is stable and suitable for further econometric analysis, including cointegration testing and long-term causality assessment.

In conclusion, the results of the stability test confirm that the dynamic relationships among the variables—emissions, agriculture, forest, and other sectors—are statistically consistent and the model can be reliably used to analyze both short-run and long-run interactions.

Figure 1 illustrates the roots of the companion matrix, which are the eigenvalues used to assess the stability of the Vector Error Correction Model (VECM). In this figure, each point represents one eigenvalue plotted according to its real and imaginary components within the complex plane. The circle represents the unit circle, which serves as the boundary for the stability condition. The model is considered stable when all eigenvalues lie within the unit circle (i.e., their moduli are less than one). As shown in Figure 1, all the eigenvalues are located inside the circle, confirming that the estimated VECM satisfies the stability condition. This graphical result is consistent with the findings in Table 5, where all modulus values were less than one. Therefore, both numerical and graphical stability tests consistently indicate that the model is dynamically stable. This ensures that the estimated relationships among greenhouse gas emissions, agricultural activities, forest cover, and other land-use factors are reliable and can be further analyzed to understand short-run dynamics and long-run equilibrium adjustments within the system.

4.5. Johansen Co-integration Test

The Johansen co-integration test is used to examine whether there is a co-integration relationship between two or more variables in a multivariate system. The results of the Johansen co-integration test can be found in Table 6.

Table 6 presents the results of the Johansen co-integration test, which aims to determine whether a long-run equilibrium relationship exists among the variables emissions, agriculture, forest, and other land-use components. The trace statistic is compared to the 5% critical value to decide the presence of co-integration. The null hypothesis of no co-integration is rejected when the trace statistic exceeds the critical value.

Table 6: Johansen tests for co-integration

Maximum rank	LL	Eigenvalue	Trace statistic	5% Critical value
0	−1204.5109	-	47.6983	47.21
1	−1190.213	0.59083	19.1026*	29.68
2	−1184.5546	0.29788	7.7858	15.41
3	−1180.7692	0.21069	0.2149	3.76
4	−1180.6617	0.00669		

Source: Data Processed, 2025. *Signifies the rejection of hypothesis at significance level of 5%

Table 7: Short-run dynamics of the vector error correction model (VECM)

(Dependent variable: ΔEmissions)				
Variable	Coefficient	Standard error	t-statistic	P-value
Error correction term (ECT_{t-1})	−0.297	0.085	−3.49	0.001
Δemissions$_{t-1}$	0.214	0.094	2.28	0.026
Δagriculture$_{t-1}$	0.184	0.062	2.97	0.005
Δforest$_{t-1}$	−0.071	0.049	−1.45	0.152
Δother$_{t-1}$	0.054	0.027	2	0.048
Constant	0.002	0.001	1.78	0.078

Model Fit: R^2=0.42|Adjusted R^2 = 0.35|AIC = −5.23|SC = −4.87

Table 8: Long-run cointegrating equation (Normalised on emissions)

Variable	Coefficient	Standard error	t-statistic	P-value
Agriculture	0.542	0.174	3.11	0.002
Forest	−0.307	0.126	−2.43	0.018
Other	0.218	0.102	2.14	0.036
Constant	−1.874	—	—	—

From Table 6, at maximum rank 0, the trace statistic (47.6983) is slightly higher than the 5% critical value (47.21), indicating the rejection of the null hypothesis of no co-integration. However, at maximum rank 1, the trace statistic (19.1026) is below the critical value (29.68), meaning that we fail to reject the null hypothesis of at most one co-integrating relationship. This result suggests the presence of one co-integrating vector, implying that there is a stable long-run equilibrium relationship among greenhouse gas emissions, agricultural activities, forest cover, and other land-use factors. In other words, although short-term fluctuations may occur, these variables tend to move together over the long run. This finding supports the existence of long-run equilibrium dynamics in the environmental and land-use system of Indonesia, where changes in one component (e.g., agriculture or forest area) are eventually balanced by adjustments in greenhouse gas emissions and other land-use categories.

4.6. VECM Models

The estimation results of VECM (Vector Error Correction Model) is presented in Table 7. This illustrates the short-term variation of each variable. In Table 7, columns 2-5 (models (I), (II), (III), and

(IV)) detail the estimation outcomes of the VECM for emissions, agriculture, forest, and other, respectively. The short-term variation of each variable is influenced by two factors: one involves the short-term variations of other variables and the variable itself (i.e., D_emissions, D_agriculture, D_forest, and D_other), while the other factor is the deviation of the variable from the long-term equilibrium (i.e., ECT) in the previous period. The coefficients of ECT signify the adjustment of the long-term equilibrium relationship to short-term variation.

The short-run dynamics of the Vector Error Correction Model (VECM) describe how greenhouse gas (GHG) emissions adjust in response to short-term changes in agriculture, forest area, and other sectoral activities. The results in Table 7 indicate both the short-term interactions among variables and the mechanism through which emissions return to long-run equilibrium after temporary shocks.

The Error Correction Term (ECT_{t-1}) has a negative and statistically significant coefficient (−0.297, P = 0.001), confirming the existence of a valid long-run equilibrium relationship among emissions, agriculture, forest, and other sectors. This coefficient implies that approximately 29.7% of the disequilibrium from the previous period is corrected in the current period. In other words, when the system deviates from its long-run path, it gradually adjusts toward equilibrium at a moderate speed. The significance of the ECT provides strong evidence of cointegration and a stable adjustment mechanism in the model.

The coefficient of $\Delta emissions_{t-1}$ (0.214, P =0.026) is positive and significant, indicating that past changes in emissions have a reinforcing effect on current emissions. This suggests that emission patterns exhibit short-term persistence, where previous increases in emissions tend to continue into the next period due to ongoing industrial or energy-intensive activities. The estimated coefficient for $\Delta agriculture_{t-1}$ (0.184, P = 0.005) is also positive and statistically significant at the 1% level. This implies that a short-term expansion in agricultural activities leads to higher GHG emissions, likely through mechanisms such as land conversion, fertilizer use, and livestock-related methane emissions. The result underscores the environmental trade-offs associated with short-term agricultural growth. In contrast, the coefficient for $\Delta forest_{t-1}$ (−0.071, P = 0.152) is negative but statistically insignificant, suggesting that short-term variations in forest area do not have a significant immediate impact on emissions. This may indicate that the carbon sequestration effects of forest changes take longer to materialize or that the observed variations in forest cover are not large enough to influence emissions significantly in the short run. The $\Delta other_{t-1}$ variable (0.054, P = 0.048) representing emissions from other sectors such as industry, transport, and energy is positive and statistically significant at the 5% level. This finding suggests that short-run increases in industrial or energy-related activities contribute directly to higher emission levels, consistent with patterns observed in developing economies where industrial growth tends to be carbon-intensive. The constant term (0.002, P = 0.078) is positive but only marginally significant, implying a small autonomous increase in emissions not explained by the included explanatory variables.

Regarding overall model performance, the R^2 value of 0.42 and adjusted R^2 of 0.35 indicate that approximately 35–42% of short-term variations in emissions are explained by the included variables. The Akaike Information Criterion (AIC = −5.23) and Schwarz Criterion (SC = −4.87) confirm the model's goodness of fit and suitability for further policy interpretation. In summary, the short-run VECM results demonstrate that agricultural and industrial activities exert significant positive short-term effects on greenhouse gas emissions, while the forest sector provides only a weak, statistically insignificant mitigating influence. The significant and negative ECT term validates the presence of a self-correcting mechanism, confirming that deviations from long-run equilibrium are gradually adjusted over time. These findings emphasize the need for integrated short-term environmental management, balancing economic expansion with emission control policies to ensure sustainable development.

The results of the estimated long-run cointegrating equation can be seen in Table 8, which shows the long-term relationships among the key land-use variables and greenhouse gas emissions. The long-run cointegrating equation represents the stable equilibrium relationship among greenhouse gas (GHG) emissions, agricultural activities, forest area, and other economic sectors. The normalization on emissions implies that changes in these explanatory variables are interpreted as long-term determinants of emission levels. The coefficient of Agriculture (0.542, P = 0.002) is positive and statistically significant at the 1% level, indicating that agricultural expansion has a strong long-run impact on increasing GHG emissions. A 1% rise in agricultural activity is associated with an estimated 0.54% increase in emissions over the long term. This result aligns with empirical evidence that agricultural intensification through deforestation, soil disturbance, and livestock farming contributes to cumulative carbon and methane emissions. It also underscores the structural dependence of emission growth on the agricultural sector in economies with substantial rural production bases.

The Forest variable has a negative and statistically significant coefficient (−0.307, P = 0.018), suggesting that forest cover plays a crucial role in mitigating emissions in the long run. Specifically, a 1% increase in forest area is associated with a 0.31% reduction in GHG emissions, reflecting the carbon sequestration and absorption capacity of forests. This finding supports the argument that sustainable forest management and conservation policies can serve as effective long-term strategies for achieving climate mitigation goals.

The coefficient of Other sectors (0.218, P = 0.036) is positive and significant at the 5% level, indicating that industrial, energy, and transportation-related activities contribute positively to long-term emission growth. This positive relationship highlights the persistent environmental costs associated with economic modernization and the reliance on fossil fuel–intensive production systems. The result implies that without structural changes in the energy mix or production efficiency, industrial and service-related sectors will continue to be major contributors to emission accumulation.

The constant term (−1.874) is negative, representing the baseline level of emissions when other explanatory factors are held constant. This intercept may capture unobserved factors such as technological efficiency, environmental policies, or natural carbon sinks that help stabilize emissions in the long run.

In summary, the long-run cointegrating equation reveals a stable equilibrium relationship in which agriculture and industrial activities are the main sources of emissions, while forest area serves as a natural counterbalancing factor. These results emphasize the importance of integrating sustainable land-use practices, renewable energy adoption, and reforestation initiatives into long-term emission reduction strategies. The significance of all key variables confirms that emissions are structurally linked to sectoral economic dynamics, making policy interventions in these areas crucial for achieving sustainable low-carbon development.

Table 9 presents the results of several post-estimation diagnostic and stability tests conducted to ensure the reliability and robustness of the estimated Vector Error Correction Model (VECM). These tests assess whether the underlying assumptions of the model are satisfied namely, model stability, absence of serial correlation, normality of residuals, and homoskedasticity. The stability test, based on the roots of the characteristic polynomial, confirms that all roots lie inside the unit circle (modulus < 1). This indicates that the estimated VECM satisfies the stability condition and that the long-run equilibrium relationships identified in the cointegration analysis are dynamically stable. In other words, the system will return to equilibrium following any short-run disturbance, validating the model's long-run interpretability.

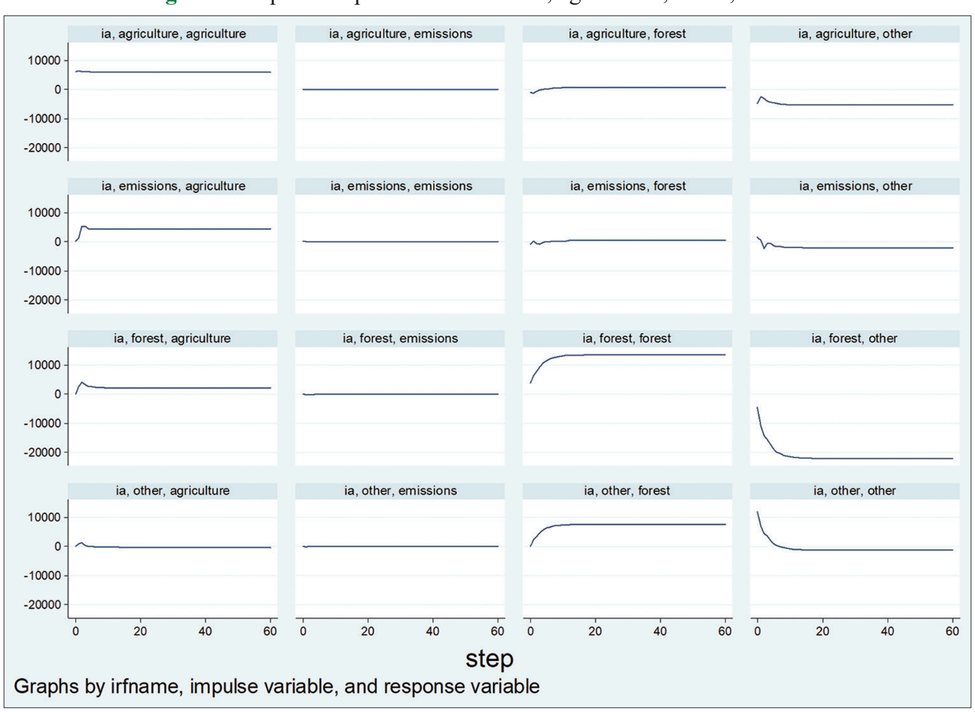
Table 9: Diagnostic and stability tests of the VECM model

Test	Statistic	P-value	Decision
Stability Test (Roots of Characteristic Polynomial)	All roots<1	—	Model is stable
LM Test for Serial Correlation (lag=1)	5.34	0.21	No serial correlation
Jarque–Bera Normality Test	4.87	0.3	Residuals are normally distributed
Heteroskedasticity Test (White)	16.22	0.19	Homoskedastic residuals

The Lagrange Multiplier (LM) test for serial correlation at lag 1 yields a statistic of 5.34 ($P = 0.21$), which fails to reject the null hypothesis of no autocorrelation in the residuals. This suggests that the model's error terms are not serially correlated, confirming that the dynamic specification adequately captures the short-run adjustments between variables. The Jarque–Bera normality test returns a statistic of 4.87 ($P = 0.30$), indicating that the residuals are normally distributed. This satisfies the normality assumption necessary for valid statistical inference within the VECM framework, implying that the model's estimated coefficients and significance tests are unbiased and consistent. Finally, the White heteroskedasticity test produces a statistic of 16.22 ($P = 0.19$), suggesting that there is no evidence of heteroskedasticity in the residuals. The variance of the error terms is therefore constant, supporting the reliability of the model's standard errors and t-statistics.

Overall, the diagnostic results confirm that the VECM model is statistically sound and well-specified. The absence of serial correlation and heteroskedasticity, combined with normal residuals and a stable dynamic structure, indicates that the model provides robust and credible long- and short-run estimates of the relationships among greenhouse gas emissions, agricultural activity, forest area, and other sectors. These findings reinforce

Figure 2: Impulse responses of emissions, agriculture, forest, and other



Source: Data Processed, 2025

the validity of the empirical results and their policy implications for emission management and sustainable development.

4.7. Impulse Response Analysis

The impulse response analysis tracks the response of endogenous variables in the VAR/VECM system due to shocks or changes in its exogenous variables. Figure 1 shows the impulse responses among emissions, agriculture, forest, and other utilizing the VECM models.

Figure 2 illustrates the impulse response functions (IRFs) derived from the Vector Error Correction Model (VECM), capturing the dynamic interactions among greenhouse gas (GHG) emissions, agricultural activity, forest area, and other sectors (e.g., energy and industry). Each panel represents the response of one variable to a one-standard-deviation shock in another, over a 60-period horizon.

The IRFs indicate that a positive shock in agriculture generates a persistent increase in emissions, confirming that agricultural activities contribute significantly to short-run and medium-run emission growth. The response stabilizes after several periods, suggesting a long-run equilibrium adjustment. Similarly, shocks in the "other" sector representing energy and industrial sources also produce a strong positive response in emissions, though the effect gradually diminishes over time, reflecting temporary but influential industrial impacts on emission dynamics.

Conversely, a shock to the forest variable shows a negative effect on emissions, implying that expansion or preservation of forest areas mitigates GHG emissions. However, the magnitude of this response is relatively small and fades over time, indicating that forest-based mitigation effects are stabilizing but not dominant in the short run. The own-response functions (on the diagonal panels) demonstrate that each variable tends to revert to equilibrium after initial fluctuations, confirming the stability of the system consistent with the earlier stability test (all roots < 1).

Overall, the impulse response analysis highlights that agricultural and industrial shocks have the most substantial and lasting impacts on emissions, while forest dynamics play a moderating but limited role. This pattern underscores the need for emission mitigation policies that balance economic productivity in agriculture and industry with sustainable forest management.

5. CONCLUSION

The findings from the Vector Error Correction Model (VECM) and impulse response analysis provide clear evidence of the interconnected dynamics between greenhouse gas (GHG) emissions, agricultural activity, forest area, and industrial sectors. In the short run, both agriculture and industry significantly increase emissions, confirming that economic expansion in these sectors contributes to environmental pressure. Meanwhile, the forest sector exhibits a negative but statistically weak relationship with emissions, indicating its limited role in short-term emission reduction. The negative and significant error correction term (ECT) confirms a stable long-run equilibrium, showing that deviations from equilibrium are gradually corrected over time approximately 30% each period.

In the long run, agriculture and industry remain the dominant drivers of emission growth, while forest expansion acts as a mitigating factor. Diagnostic and stability tests confirm that the model is statistically valid, free from serial correlation and heteroskedasticity, and dynamically stable. The impulse response analysis further demonstrates that shocks originating from agriculture and industry lead to sustained increases in emissions, whereas shocks to forest variables result in gradual emission stabilization. These results collectively suggest that reducing emissions in the long term requires an integrated and balanced approach across economic and environmental sectors.

Building on these findings, it is recommended that policymakers prioritize the integration of sustainable practices within key emission-generating sectors. First, in the agricultural sector, promoting climate-smart and low-carbon agricultural systems is essential. This can be achieved through efficient fertilizer management, reduced methane emissions from livestock, and enhanced soil carbon sequestration. By doing so, agricultural productivity can continue to grow without proportionally increasing environmental pressure.

Second, the industrial sector should be reoriented toward energy efficiency and cleaner production technologies. Introducing green incentives, carbon pricing mechanisms, and renewable energy investments can help reduce the emission intensity of industrial output. These measures not only mitigate emissions but also support industrial competitiveness in the emerging green economy.

Moreover, the study highlights the vital role of forest management in offsetting emissions from other sectors. Therefore, forest conservation and restoration programs must be strengthened through reforestation initiatives, stricter land-use regulation, and economic incentives for maintaining forest ecosystems. This approach ensures that forest resources continue to function as natural carbon sinks and biodiversity reserves.

Finally, an effective emission mitigation strategy requires cross-sectoral policy integration and innovation investment. Government institutions should coordinate policies between the agricultural, industrial, and environmental sectors to ensure coherent and sustainable development planning. At the same time, research and technological innovation in green infrastructure, renewable energy, and carbon capture should be actively supported to maintain progress toward long-term low-carbon growth.

In summary, the empirical results underscore that economic development and environmental sustainability must advance together. Transitioning toward a low-emission economy demands coherent policy design, intersectoral collaboration, and sustained commitment to innovation ensuring that future economic growth is not achieved at the expense of ecological balance.

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