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Examining the Impact of Energy Use, Economic Growth, and Forest Area on CO_2 Emissions: Consequences for Achieving the SDGs

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ABSTRAK

Climate change can be caused by both natural and human activities. Human activities are the main factor causing climate change that is getting worse such as deforestation, industrialization, transportation, and so on. Climate change that occurs continuously can cause various health risks, global food security, decreased biodiversity, and environmental damage to economic development. Climate change also needs to be studied in the application of SDGs to realize sustainable development targets. The purpose of this study is to examine the relationship between economic growth, energy consumption, and forest area to CO_2 emissions in Indonesia from 1990-2022 and find out what the implications are with the achievement of SDGs on climate change. This study applies the VECM analysis method to get an overview of the long-term balance and short-term relationship of the four variables. The results obtained are that forest area only affects CO_2 emissions in the long term, while economic growth only affects CO_2 emissions in the short term. Meanwhile, the energy consumption variable affects CO_2 emissions in both the short and long term. Therefore, handling from various parties and policies from the government are needed to realize environmentally friendly development to achieve sustainable development goals in the future.

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INTRODUCTION

Sustainable Development Goals (SDGs) is an agreement at the 2015 UN General Assembly related to the improvement of the Millennium Development Goals. The goal is for people's welfare to increase sustainably in the economic field, for the sustainability of people's social life and environmental quality to be maintained, and for development to be inclusive and managed so that intergenerational life can be of quality. The SDGs are targeted to be completed by 2030. Of the 17 goals of the SDGs, the 13th goal is related to tackling climate change. One of the targets of the 13th SDGs is the integration of climate change anticipation with national policies, strategies, and planning.

Climate change needs to be assessed in the implementation of the SDGs because it can affect human life in the future. Climate change includes an increase in carbon dioxide, changes in temperature, rainfall, sea level, and so on (Duchenne-Moutien & Neetoo, 2021). Climate change can be influenced by both natural phenomena and human activity itself (Kartiasih & Setiawan, 2020; Pribadi & Kartiasih, 2020). Human activities that can affect climate change include deforestation, industrialization, etc (Arwan, 2022). Continued climate change may pose risks to health, the global food situation, and economic development (Legionosuko et al., 2019). The handling of climate change has 5 targets, one of which is the integration of climate change anticipation into national policies, strategies and planning as previously explained. The target also contains several metadata indicators, one of which is the Greenhouse Gas (GHG) emission reduction reporting document. GHGs can come from CO_2, methane, nitrous oxide, CFCs, transportation, industry, etc (Legionosuko et al., 2019). Meanwhile, according to the BPS SDGs Indicator Study, the sources of GHG emissions include energy, industry, agriculture, forests, transportation, buildings, and others. According to the World Resources Institute, Indonesia is among the eight largest contributors to GHG emissions after 2020. This is reinforced by European Commission data that Indonesia's GHG emission volume in 2022 reached 1.24 giga tons and this figure increased by 10% compared to 2021.

Based on the previous description, CO_2 is one of the GHG contributors. Factors affecting CO_2 emissions in each country are different (Rahman et al., 2022). Based on the scatter plot graph of GDP per capita and CO_2 emissions of countries in the ASEAN region in 1980-2014, it can be seen that there is a unidirectional positive relationship between GDP per capita and CO_2 emissions. This shows that GDP per capita affects CO_2 emissions, but not the other way around (Nurbandi & Astuti, 2019). However, according to Pejovi et al. (2021) a decrease in CO_2 emissions can be supported by an increase in GDP (Rahman et al., 2022). Based on the BPS SDGs Indicator Study, CO_2 intensity originating from the electricity sector, the increase in global temperature is limited to 2 degrees Celsius so that this sector can approach zero carbon. In addition, the transportation sector also plays an important role in CO_2 intensity. CO_2 emissions from this sector depend on the size of a region, the population, and the level of economic activity that occurs in the region. The larger the area, the larger the population and thus the more economic activity. This can cause CO_2 emissions to tend to increase as well.

According to the Global Carbon Project (2023), globally as much as 85% of CO_2 emissions are caused by human activities from the combustion of coal, oil and natural gas and are the main cause of increasing global GHG emissions. The production of global carbon emissions due to human activities is dominated by fossil fuel combustion and deforestation

(Begum et al., 2020). In 2022, Indonesia was recorded as the world's 5th largest CO_2 emitter after Brazil and ranked first as the largest cumulative carbon emitter in ASEAN. In Indonesia itself, from 1950 to 2021, the greenhouse gas (GHG) emissions produced have increased very significantly to reach sixty-three times. Meanwhile, according to Ahdiat (2023), in 2022 Indonesia's greenhouse gas emissions increased by 10% compared to 2021, as well as being a new record high because it has the largest annual percentage increase compared to other countries. Until 2030 and beyond, it is predicted that GHG emissions will continue to increase. From 1990 to 2022, total carbon emissions in Indonesia had an upward trend every year, meaning that the problem of CO_2 production in Indonesia has always increased and fluctuated quite a lot. The increase in CO_2 emissions was at its highest peak in 1997-1998. The forestry and energy sectors are the largest contributors to overall GHG emissions in Indonesia. The forestry sector is the dominant contributor to CO_2 emissions due to deforestation, namely deforestation to be converted into industrial or residential areas. Power plants, the transportation sector, and the energy-consuming industrial sector, especially fossil energy, are the causes of the increase in CO_2 emissions in 2012-2017. This increase in CO_2 emissions has increased the risk of extreme climate change (Rahmayani, 2021). The production of CO_2 emissions in Indonesia is caused by human activities (Labiba & Pradoto, 2018). Human activities that are a factor in increasing CO_2 emissions include activities in the economic, industrial, transportation and other sectors that contribute a lot to increasing GHG production.

According to the Forest Resources Assessment (2020), a forest is a land area of more than 0.5 hectares with trees that are more than 5 meters tall and more than 10 percent canopy cover, or trees that are capable of reaching this threshold in situ. This does not include land that is predominantly agricultural or urban. Information on forest areas and how they change over time is critical to measuring progress towards achieving sustainable development (SDGs). Forests are prioritized in the SDGs because of their significant contribution to food security and livelihoods and the many ecosystem products and services they provide. SDG 15 (Terrestrial Ecosystems), places forests at the center of terrestrial ecosystem sustainability, aiming to protect, restore, and promote sustainable use of terrestrial ecosystems and forest management, combat desertification, halt land conversion, and halt biodiversity loss (FAO, 2020). However, forest areas often do not receive attention from various parties. In fact, the global forest area always decreases every year. For 10 years from 2010 to 2020, the average loss of forest area was 5.17 million ha and Indonesia ranked third in the top 10 countries with the highest average loss of forest area in the world in 2010-2020 (FAO, 2020). This shows that Indonesia is experiencing a crisis of annual forest area loss or deforestation. Deforestation is the main source of carbon (CO_2) emissions caused by human activities, second only to the burning of fossil fuels. This human activity has reduced the total hectares of available forest cover and resulted in significant land use change worldwide (Van Der Werf et al., 2009). Meanwhile, non-forestry land uses, such as logging to convert to agricultural land, release large amounts of carbon (CO_2) into the atmosphere (Parajuli et al., 2019). Thus, it is clear that human activity is the main factor that causes deforestation and causes many environmental problems such as landslides, floods, forest fires and global warming due to excessive carbon emissions, so it needs to be a priority for all groups, especially the government, to make policies to overcome environmental problems due to the decline in forest area.

On the other hand, economic growth in Indonesia is in the spotlight amid the slowdown in the global economy after the Covid-19 pandemic because it shows a relatively stable movement. The Central Bureau of Statistics (2023) through the Official Statistics News (BRS) said that Indonesia's economic growth rate in the third quarter of 2023 experienced a slow increase of 5.05% compared to the second quarter of 2023 and 4.94% compared to the third quarter of the previous year. This increase provides a positive picture of the sustainability of economic recovery efforts after the Covid-19 pandemic while providing hope for better growth in the future. In line with this, the World Bank ranks Indonesia 16th out of all countries in the world with a GDP value of US$1.32 Trillion in 2022. The rise of industrialization in various sectors is the main driver of Indonesia's economic growth so that it can reach this figure. Broadly speaking, economic growth is closely related to the use of natural resources and their impact on the environment. Therefore, efforts to stimulate economic growth with environmental concerns are a challenge for Indonesia. This means that everything related to improving the community's economy must have the least possible impact on the environment. If economic activities are not managed properly, the possibility of environmental damage in the future becomes even greater. The impact that may occur due to these conditions is the creation of the greenhouse effect. CO_2 emissions are one of the dominant compounds that make up greenhouse gases that can cause abnormal behavior in the climate and global warming. Based on data from the European Commission (2023), the volume of Indonesia's greenhouse gas emissions reached 1.24 Gt CO_2e in 2022. This figure increased by about 10% compared to the previous year and is the highest greenhouse gas emission record since 1970. In line with this, the Ministry of Industry of the Republic of Indonesia also said that the total GHG emissions from the industrial sector reached 238.1 million tons of CO_2e in 2022. This figure comes from various energy needs, such as energy use for industry, industrial process needs and product use, to waste from the industry itself. By looking at the amounts of emissions generated by economic activities in Indonesia, especially the industrial sector, it is necessary to manage the balance between economic activities and their impact on the environment.

Given the growing economic activities, energy plays a crucial role in sustaining a country. Currently, energy consumed by the global community is divided into several types, such as electricity, gasoline, diesel, coal, and so on (Kartiasih et al., 2012). All of these types of energy are closely related to the survival of society. Therefore, the increase in energy consumption is determined by the activities of the society itself, including economic activities (Hartono et al., 2023). The rapid economic development of a country cannot be separated from the need for energy supply to support its economic activities. Along with Indonesia's economic growth, its energy consumption is also increasing. According to the Ministry of Energy and Mineral Resources (2021), energy consumption in Indonesia increased slightly compared to the previous year, reaching 909.24 million BOE. The report also stated that the industrial sector contributed 34.93% of the total energy consumption or around 317.57 million BOE. This means that the level of energy consumption in Indonesia will increase as economic growth increases. The implication of this condition is that natural resources will be overexploited and lead to environmental damage and climate change. According to the Indonesia Energy Transition Outlook (IETO) 2022 released by the Institute for Essential Services Reform

(IESR), the energy sector is the second largest emitter, contributing around 34% of total emissions in 2019. This means that a mechanism for managing and reducing emissions is needed to realize sustainable development within the scope of the SDGs.

Unlike previous studies, this research has several important objectives, namely implementing and validating the Environment Kuznet Curve (EKC) hypothesis on the relationship between economic growth and carbon emissions (CO_2) in the period 1990 - 2022 in Indonesia. Then, see the effect of forest area, economic growth, and energy consumption on CO_2 emissions for the period 1990-2022 in Indonesia. Finally, forecast the likelihood of achieving SDGs goals, especially those related to climate change, by 2030 based on the data collected. This research implements the Vector Error Correction Model (VECM) analysis method to see the impact of forest area, economic growth, and energy consumption on CO_2 emissions in Indonesia in the short and long term, as well as forecasting for each variable use.

THEORETICAL BASIS

Rapid economic growth that is not matched by proper management of CO_2 emissions can cause environmental damage in the future. Global warming and climate change are just a few examples of the possible consequences of such conditions. As discussed earlier, an increase in CO_2 emissions has a positive relationship with the energy demand that supports a country's economic growth. Therefore, the economic growth of a country must always lead to environmental damage. One method that can be used to model environmental performance is the Environmental Kuznet Curve (EKC). The EKC shows the relationship between economic growth and environmental degradation as an inverted U-curve (Kuznets, 1955). Broadly speaking, the curve divides a country's economic journey into three parts: the beginning of economic development, the turning point, and the end of economic development (Leal & Marques, 2022). This means that an increase in environmental damage is accompanied by an increase in economic growth until a certain point (turning point). At that point, environmental damage will gradually decrease as economic growth increases.

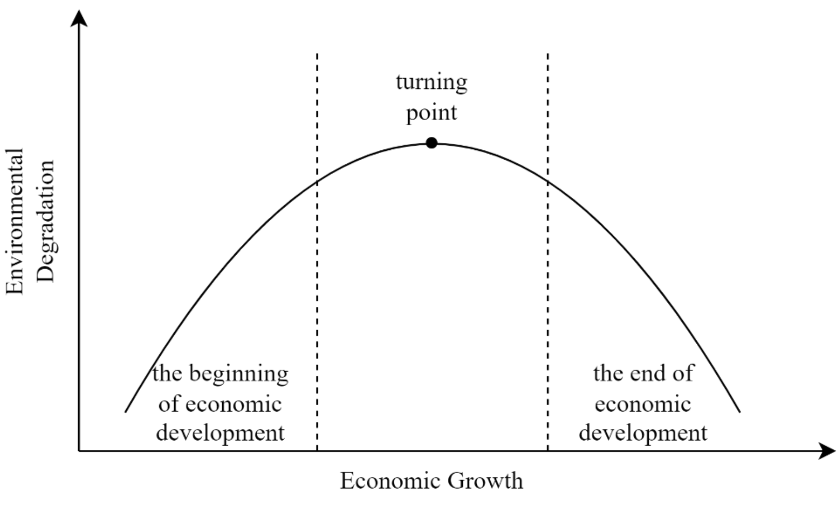


Figure 1. Illustration of Kuznet Curve (Environmental Kuznet Curve)
Source: Leal & Marques (2022)

Nowadays, the EKC hypothesis has been widely applied in studies around the world, especially to examine the relationship between economic growth and the environment. EKC can provide knowledge to support a country's energy efficiency (Kisswani & Fikru, 2023). The study attempted to validate the inverted U-curve to see the relationship between electrical energy consumption and people's income in five ASEAN countries, including Indonesia. Similar research was also conducted by Oztur dan Sarkodie (2020) who stated that an increase in per capita income can increase energy consumption which has a long-term impact on the environment based on the EKC hypothesis, energy efficiency indicators and energy consumption. On the other hand, EKC is also used to analyze the relationship between increasing GDP per capita and CO_2 emissions of a region Adzawla et al. (2019); Haug & Ucal (2019); Mahmood et al. (2021). The findings of these studies suggest that an increase in GDP can lead to an improvement in environmental quality if balanced with innovations to reduce existing carbon emissions.

Research on the causality relationship between economic growth, energy consumption, and CO_2 emissions in several countries in ASEAN has been conducted by Saboori & Sulaiman (2013). By using the VECM and ARDL method approaches, the results obtained carbon emissions and energy consumption of countries in ASEAN have a positive relationship both in the short and long term. This study also confirmed the conformity with the Kuznet curve hypothesis for the relationship between economic growth and CO_2 emissions. Arfaoui (2016) showed that there is no significant relationship between energy consumption and economic growth for some Arab countries. Then, according to Palamalai et al (2015) CO_2 emissions and economic growth have a positive causal relationship. The results also indicate that there is an effect of foreign trade on energy consumption in the long run. Some similar studies related to the relationship between economic growth factors or energy consumption on carbon emissions (CO_2) have also been conducted by previous studies Jian et al. (2019); Kasman & Duman (2015); Rahmayani (2021); Saidi & Hammami (2015);Kartiasih & Setiawan (2020); Bilan et al. (2019); Anwar et al. (2020) .

Many studies have tested the Kuznet hypothesis regarding the relationship between environmental damage and economic growth or economic activity. However, studies that discuss the link between forest area and carbon (CO_2) emissions have not been conducted in Indonesia. Forests are natural ecosystems that are known to absorb carbon (CO_2) naturally but are not given much attention today. Then, Indonesia itself with an area dominated by water but included in the ranks of countries with the largest forest area in the world (Khairani et al., 2023; Latifa et al., 2023), which is ranked eighth (FAO, 2020). Indonesia's forest area is around 95.6 million hectares in 2020 (KLHK, 2020) and ranks first in ASEAN. Thus, an up-to-date study on the relationship between forest area and CO_2 emissions in Indonesia needs to be conducted to obtain an overview and considerations for stakeholders in making policies.

Fauzi (2017) has conducted research on the effect of energy consumption, forest area, and economic growth on CO_2 emissions in several countries in 6 countries in ASEAN. The results showed that every one percent increase in forest area led to a decrease in carbon emissions (CO_2) by 0.04% (tons per capita). Then, Sodri & Garniwa (2016) examined the relationship of urbanization to energy consumption which increases the production of CO_2 emissions using the VECM model. Other studies that investigated the relationship between economic growth and forest area to CO_2 emissions were conducted by Begum et al. (2020) dan Raihan & Tuspekova (2022). Then, research on the effect of forest degradation on carbon emissions was conducted by Henders et al. (2015); Rappaport et al. (2020).

Monika (2015) identified what influences CO_2 emissions using the VECM model. This model is an adjusted VAR model because the data is not stationary and cointegrated. It was found that the variables of industrial value added, ODA, GDP, City Population Growth (CDP) have a significant influence on CO_2 in the long run. The variables of industrial value added and GDP also have a significant influence on CO_2 in the short term. Alagirisamy & Manigandan (2021) examined the relationship between CO_2 emissions, energy use, GDP, and population growth that occurred in India from 1980 to 2018. In his research using the VECM and ARDL approach models. It was found that there is a long-term equilibrium relationship between energy use, GDP, population growth, and CO_2. As much as 58.4% of future fluctuations in CO_2 emissions are caused by energy use, 2.8% are caused by GDP, 0.43% are caused by population growth. This was also done by Jian et al. (2019) who studied the impact of economic growth, financial development, and energy consumption on CO_2 emissions in China from 1982 to 2017 using the VECM approach. It was found that financial development and energy consumption have a significant positive impact on CO_2 emissions. Economic growth can reduce CO_2 emissions in the long run.

METHODS

Data

This study uses time series data totaling 33 observations with an annual period from 1990 to 2022. The data was obtained through the Our World in Data website and the World Bank as secondary data. In order to analyze the data, this research uses descriptive and inferential analysis in the form of time series analysis. Descriptive analysis was used to provide an overview of the development of forest area, economic growth, energy consumption, and CO_2 emissions from 1990 to 2022 using graphs. Then, Eviews 12 software is used as a data processing tool that has been collected.

Inferential analysis in the form of time series analysis using the VECM model. The VECM model is used to see the causality pattern between GDP, energy consumption, and forest area on CO_2 emissions. This model is a restricted form of VAR that is suitable for use when the data collected is not stationary at the level but has cointegration. VECM is able to estimate the long and short-run effects between variables from the time series data used.

Table 1. Variable Description dan Notation

Name of Variable	Notation	Description

Economy Growth	GDP	Annual percentage growth rate of GDP at market prices based on constant local currency. Aggregates are based on 2015 base year prices, expressed in US dollars.
Energy Consumption	EC	The use of primary energy before it is converted into end-use fuels such as electricity or gasoline for transportation. Expressed as a percentage of energy consumption per capita.
Forest Area	FA	Land greater than 0.5 hectares consisting of trees greater than 5 meters in height and more than 10 percent canopy cover, or trees capable of reaching these thresholds in situ. Expressed as a percentage of forest area.
CO_2 emission	CO2E	Total annual carbon dioxide (CO_2) emissions, due to land use change and fossil fuel use measured in tons.

Source: World Bank, Our World in Data

Methodology

The VAR method used in this study is the Vector Error Correction Model (VECM) to test the four variables, namely economic growth, energy consumption, forest area, and CO2 emissions. VECM is also often referred to as a restricted VAR model so that in this study the VAR model will change to a VECM model using yt-1 (first different). According to Pratiwi et al. (2022) there are eight steps in analyzing time series data using the VECM model, including Stationarity Test, Optimal Lag Length Test, Stability Test, Cointegration Test, Granger Causality Test, VECM Model, Impulse Response Factor (IRF) Test and Variance Decomposition (VD).

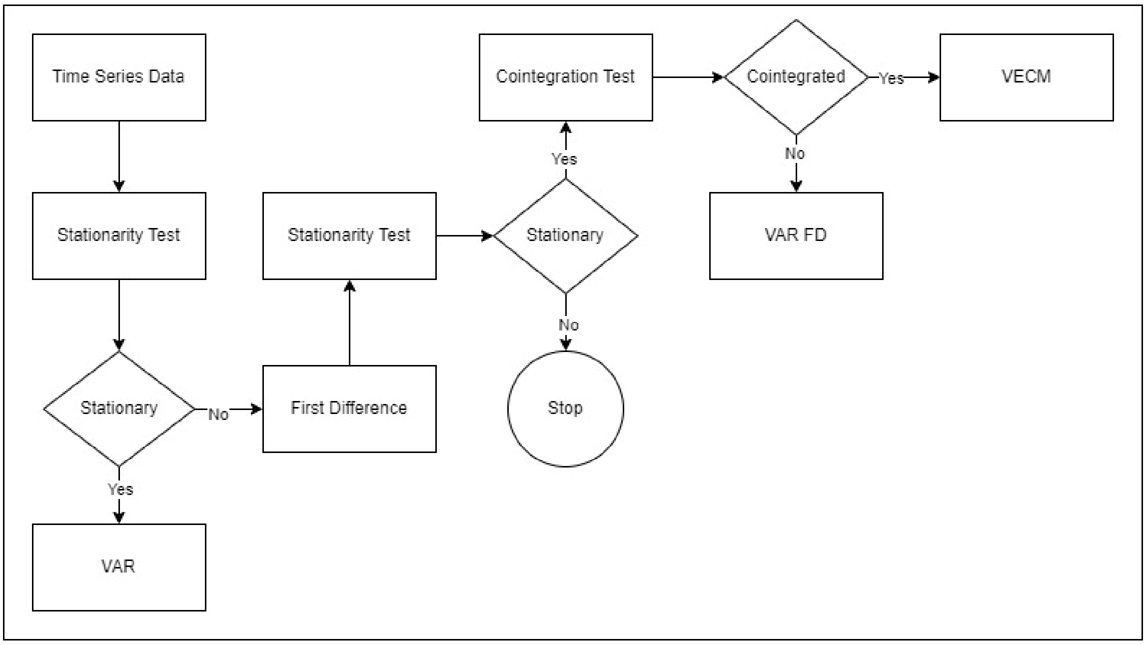


Figure 2. Research Framework

Stationarity Test

Data stationarity testing plays a vital role in time series data analysis. This test helps determine the analysis model suitable for the data used in a study. A time series data is considered stationary if the data's mean, variance, and covariance are constant at each period (Ziegel & Enders, 1995). This test contributes to seeing unit roots that can cause spurious regression, a regression model that looks statistically good, but the relationship between variables is not significant. Therefore, a follow-up to this test is usually a process of differentiation or transformation of the data until stationary data are obtained. In this study, the stationary test is conducted using the Augmented Dickey-Fuller (ADF) test, which will compare the t-statistic value with the critical value generated by the method. Thus, the results obtained can be used as a reference in choosing the suitable model at the following research stage.

Optimal Lag Determination

According to Jian et al. (2019) the optimal lag is determined before the cointegration test. The optimal lag length is determined based on AIC (Akaike Information Criterion), SC (Schwarz Information Criterion), LR (Likelihood Ratio), FPE (Final Prediction Error), and HQ (Hannan-Quinn information criterion). The smallest value is determined by the optimal lag based on AIC, SC, and HQ.

Stability Test

Stability testing is also crucial in conducting analysis using VAR / VECM. This test is carried out to validate the VAR / VECM model's stability (Islam & Hossain, 2015). Model stability is crucial because it will determine the model's output. High estimation bias and low level of validity are a few examples of the impact of the instability of the proposed model. As a result, the IRF and FEDV values do not match the actual situation. A VAR/VECM model is said to be stable if the value of the inverse roots of AR / AR characteristic of the inverse roots of its polynomial has a modulus of less than one in the AR roots table. The unit circle shows that the modulus point is inside it (Ziegel & Enders, 1995). The model is stable if most moduli are inside the unit circle. Conversely, the model becomes unstable if most modulus points are outside the unit circle. If the VAR/VECM model is unstable or has low stability, then the estimation results using the VAR/VECM model become spurious or dubious.

Cointegration Test

The cointegration test aims to test whether the variables in the study have a long-term relationship even though the variables are not stationary (Purwaning Astuti & Juniwati Ayuningtyas, 2018). The cointegration test is conducted after the unit root test with the null hypothesis that no cointegration exists. This null hypothesis is rejected when the p-value is less than the significance level used. The cointegration test with the Johansen approach can be used in 2 ways: trace and maximum eigenvalue. If the statistical value of both is more than the critical value, then there is cointegration (Jian et al., 2019).

Granger Causality Test

Causality analysis is one of the most useful statistical tests in VECM modelling to determine short-term and long-term relationships. The Granger causality test is one approach that can be utilized to see the short-term relationship between variables. This test determines a reciprocal relationship between variables, either unidirectional, bidirectional or no relationship at all (Gujarati & Potter, 2008). In other words, the Granger causality test can help determine which variables affect and are affected by other variables in the model. In this study, the Granger causality test is used to see the relationship between forest area, economic growth, and energy consumption on CO_2 emissions in Indonesia. The test level is 0.05, with the optimum lag length determined based on the best VECM model.

VAR/VECM Model

The Vector Autoregressions (VAR) model is a model that contains simultaneous equations of several endogenous variables at once. Variables in VAR are explained by the value and lag of the variable itself and other variables contained in the model (Gujarati & Potter, 2008). Stationary data characteristics at the level are essential assumptions in the VAR model. Therefore, the VAR model is unsuitable for data that is not stationary at the level. Another approach that can be used to address these conditions is the Vector Error Correction Model (VECM). This study uses the VECM model to see the role of forest area, economic growth, and energy consumption on CO_2 emissions. That condition suitable to data that has been collected has stationary characteristics at the first differentiation, and the variables are cointegrated. The following presents the VECM model used.

$$\Delta CO2E_t = A_{01} + \sum_{i=1}^{k} \Gamma_i \Delta FA_{t-i} + \sum_{i=1}^{k} \Gamma_i \Delta GDP_{t-i} + \sum_{i=1}^{k} \Gamma_i \Delta EC_{t-i} + \sum_{i=1}^{k} \Gamma_i \Delta CO2E_{t-i} + (\alpha\beta^T)_{CO2E} Y_{t-1} + \varepsilon_{CO2Et} \qquad (1)$$

Based on the above equation, A_0 is the intercept vector, Γ_i is the regression coefficient matrix, α is the speed of adjustment, β^T is the long-run coefficient matrix, and ε_t is the error term of the above equation.

Impulse Response Function (IRF)

Analysis with the VAR/VECM method has advantages over other estimation methods because, in the VAR/VECM method, researchers can determine changes in endogenous variables due to the influence of changes in errors or changes in variables in the model. The response of a variable due to a shock to that variable in the model and its effect on the variable itself or other variables can be seen from the impulse response function (IRF) (Ziegel & Enders, 1995). The shock that occurs in the i-th variable affects itself and other variables in the model through the dynamic lag structure in VAR/VECM. IRF is used to see the contemporaneous effect of a dependent variable if it gets a shock or innovation from the independent variable by one standard deviation. This study uses IRF to identify the shock in the VECM model caused by economic growth, energy consumption, forest area, and CO_2 emissions and which variables are most significant in influencing other variables.

Forecast Error Decomposition of Variance (FEDV)

Another helpful analysis in revealing the relationship between variables in the VECM system is the forecast error decomposition of variance (FEDV) (Ziegel & Enders, 1995). FEDV is usually utilized to measure how much a variable contributes to explaining the variance of other variables as well as itself. In the context of VAR/VECM, the proportion of the impact of changes in a variable can be seen when experiencing a shock or change to the variable itself in a period. Then, variance decomposition plays a role in breaking down the variance of the forecasting error into components that can be associated with each endogenous variable in the model. This method can also see the strengths and weaknesses of each variable in influencing other variables over a long period. Therefore, FEDV can estimate the variance of a variable's error, i.e. how much the difference between before and after a shock occurs, either by the variable itself or other variables.

Forecasting

Before forecasting using the VECM model, conducting several classical assumption tests is necessary to determine whether the model formed is the best. The best model (fulfilling classical assumptions) will provide estimation results close to the actual value or with a small error. Some classical assumptions that need to be met by the model's residuals include non-autocorrelation, homoskedasticity, and non- and multivariate normality.

RESULTS AND DISCUSSION

Descriptive Statistics

The summary statistics table shows differences in the range of values and units of each variable used. This difference requires transformation first before further analysis is carried out. Natural logarithm transformation is used to eliminate significant variance differences between variables. Therefore, the transformation is only carried out on the CO2E and EC variables because the variance of these variables is more significant than the others.

Table 2. Summary of Research Variable Statistics

	CO2E (Ton)	**GDP (%)**	**EC (Kwh)**	**FA (%)**
Mean	969451096	4.70	6199.62	54.64
Median	898742500	5.17	6224.94	53.43
Standard Deviation	409250246	3.72	1576.95	4.90
Maximum	2433445600	8.22	9854.46	65.44
Minimum	462433440	-13.13	3294.79	47.65

Observation	33	33	33	33

Source: World Bank, Our World in Data, (processed)

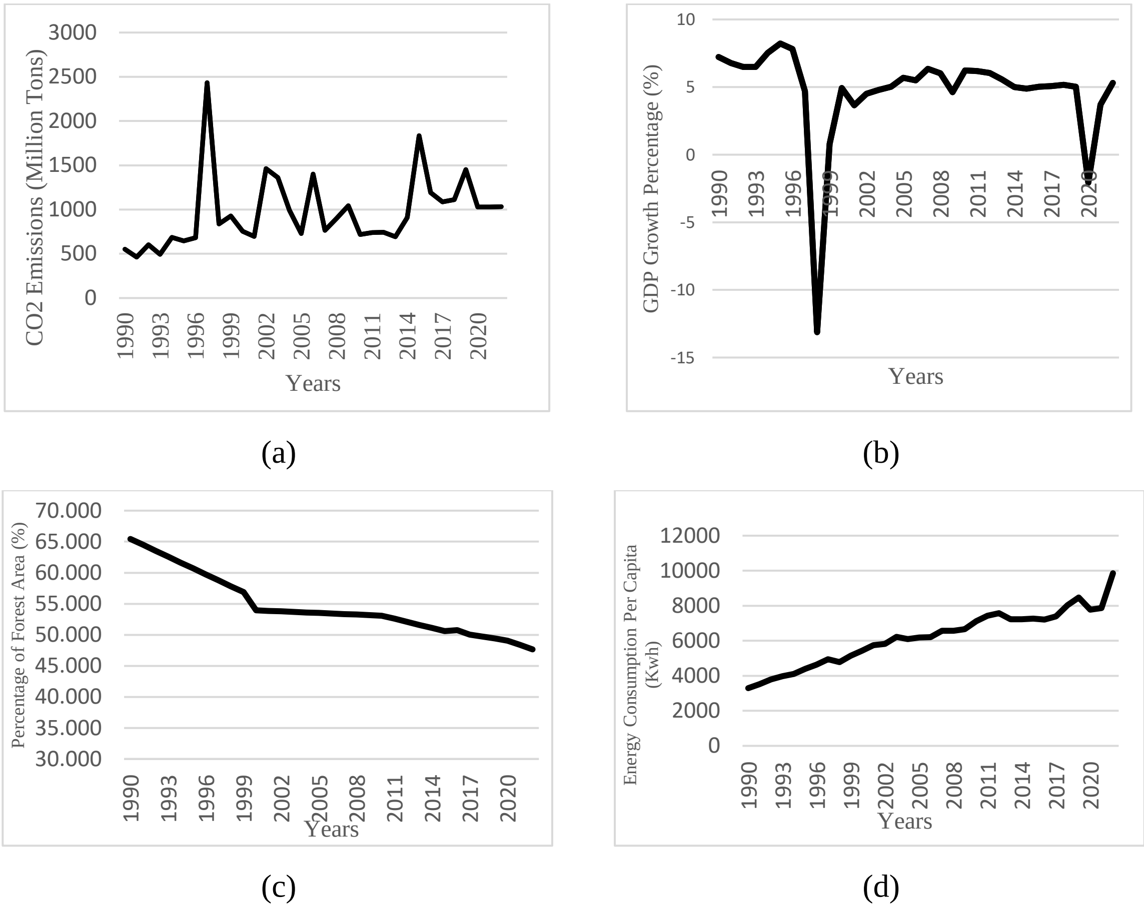


Figure 3. (a) Total CO_2 Emissions (b) Percentage of GDP Growth, (c) Forest Area, (d) Per Capita Energy Consumption from 1990-2022 in Indonesia.
Source: World Bank, Our World in Data, (processed)

The figure shows that CO_2 emissions have fluctuated from 1990 to 2022. Meanwhile, GDP growth experienced a very sharp decline in 1998. This condition was due to the 1998 recession caused by the collapse of the government, which resulted in many riots. In addition, the events 1998 also led to the closure of many jobs and a reduction in the workforce, resulting in a higher poverty rate. The decline occurred again in 2020, but not as sharply as in 1998 due to the COVID-19 pandemic, which paralyzed the community's economy. Then, it started to improve again in 2021. In terms of forest area from 1990 to 2022, it continued to decline. This can be caused by the many conversion of forests into settlements and industries. The forest conversion is driven by the increasing number of people every year. In addition, per capita energy consumption has continued to increase for 33 years. This is because more and more people use electricity for lighting and daily activities. The number of people who own motorized vehicles also affects the increasing gasoline supply, causing energy consumption to increase yearly. Both of these drive the increasing exploitation of coal and petroleum. It is also supported by the lack of use of renewable energy, which can only meet 10% of existing energy needs.

Relationship between Economic Growth and CO_2 Emissions in Indonesia

In order to validate the existence of an inverted U curve by the Kuznet hypothesis on the relationship between economic growth and CO_2 emissions, data visualization using scatter diagrams was conducted. The data used are total CO_2 emissions as the Y-axis and the percentage of GDP growth per year as the X-axis. Through plot visualization, the pattern of the data relationship can be further understood. Based on Figure 4, the relationship pattern between total CO_2 emissions and GDP growth per year in Indonesia from 1990 - 2022 shows a pattern that tends to be random and fluctuating. In fact, in specific periods, some data deviate far from the others, such as in 1998 due to the economic recession. This condition shows that the increase in CO_2 emissions was not significantly influenced by economic growth in that period. In addition, the curve also does not show a turning point that causes CO_2 emissions to decrease as economic growth in Indonesia increases. The lack of observations and unknown factors may cause this condition. In other words, in the 1990-2023 period, the relationship between economic growth and CO_2 emissions in Indonesia has yet to fulfil the Kuznet hypothesis.

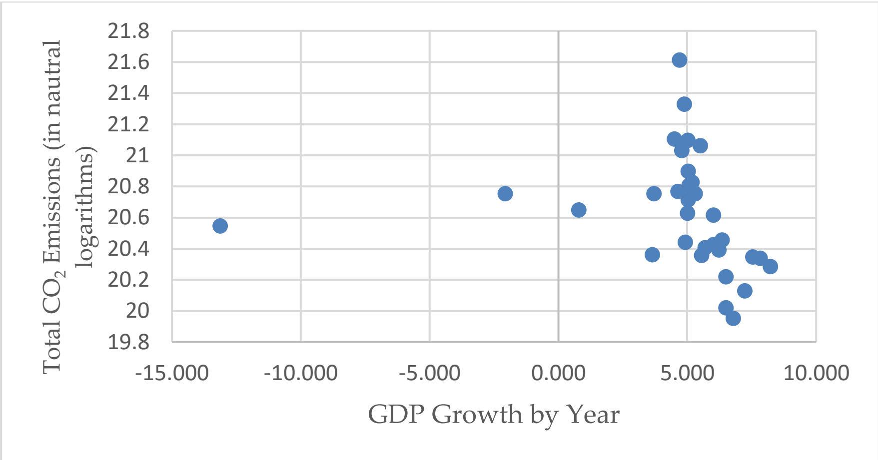


Figure 4. Relationship Curve between GDP Growth per Year and CO2 Emissions in 1990-2022 in Indonesia.
Source: World Bank, Our World in Data, (processed)

Stationarity Test

The stationarity test was conducted using the Augmented Dicky Fuller (ADF) unit root test. Each variable is tested for stationarity at the level. The null hypothesis used in this test is that there is a unit root in the tested variable. If the absolute value of the t-statistic is less than the critical value or the p-value is more than the significance level used, it is not significant and fails to reject H_0. With this decision, the variable is not stationary, so the stationarity test can be repeated in the first differential.

Table 3. Stationarity Test Results

Variable	Level	Description	*First difference*	Description
GDP	-4.162 (0.002)	Stationer	-5.766 (0.000)	Stationer
LNEC	-2.207 (0.207)	Non-Stationer	-4.868 (0.000)	Stationer
FA	-2.937 (0.052)	Non-Stationer	-3.913 (0.005)	Stationer
LNCO2E	-4.068 (0.003)	Stationer	-8.658 (0.000)	Stationer

Source: Eviews 12 output (processed)

From Table 3, the four variables tested for stationarity at the level; two variables are not stationary. LNEC (energy consumption) and FA (forest area) are the two variables. Then, the stationarity test was carried out again on the LNEC and FA variables in the first difference, and it was found that the variables were stationary. Thus, all four variables are stationary at first difference.

Optimum Lag Determination

The stage that must be fulfilled in analyzing using VECM is determining the optimal lag. The problem, if the lag length is too small, is that the model cannot explain the relationship between variables well. Meanwhile, if the lag length is too large, it causes the free degree value to become too large, making the model inefficient. The optimum lag length is seen from several criteria, including LR, FPE, AIC, SC, and HQ values.

Table 4. Optimum Lag Test Results

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-81.164	NA	0.0034	5.677	5.864	5.737
1	-61.892	32.12	0.0027	5.459	6.393	5.758
2	-23.084	54.33*	0.0006*	3.938*	5.620*	4.476*

Source: Eviews 12 output (processed).

The results of testing the optimum lag on the data used are shown in the table above. From table 4, it can be seen that the five criteria show significance at the 2nd lag so that the optimal lag length to be used in the next stage of analysis is 2. Due to the LR, FPE, AIC, SC, and HQ criteria being significant at lag 2. In other words, all variables in the model affect each other not only in the current period, but all variables are interrelated up to 2 previous periods.

Model Stability Test

A VAR/VECM model is said to be stable if the value of the inverse roots of its polynomial characteristics has a modulus whose value is less than one in the AR roots table and the unit circle shows that the modulus point is inside it (Ziegel & Enders, 1995b).

Table 5. Stability Test Results

Root	Modulus
0.0333 - 0.9315i	0.9321
0.0333 + 0.9315i	0.9321
-0.6296 - 0.5011i	0.8047
-0.6296 + 0.5011i	0.8047
0.7301	0.7301
0.0485 - 0.5153i	0.5176
0.0485 + 0.5153i	0.5176
0.0881	0.0881

Source: Eviews 12 output (processed).

Based on table 5, it can be seen that all modulus values in the table are less than 1. So, it can be concluded that the model used is stable. Then, from Figure 4, it can be seen that all modulus points are inside the unit circle, so it is also proven that the model used is stable.

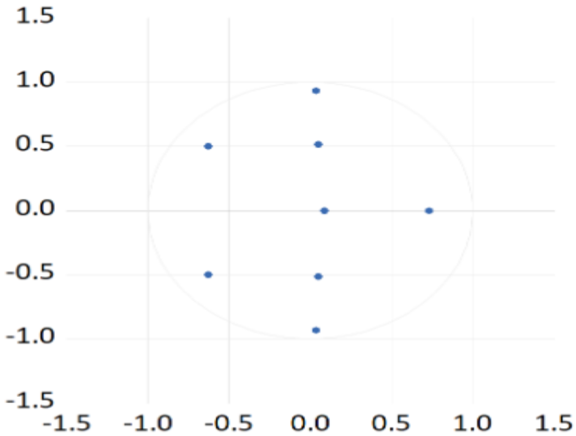


Figure 4. Stability Test Results with Unit Circle
Source: Eviews 12 output (processed).

Cointegration Test

In order to determine a suitable model for analyzing the available time series data, a cointegration test between variables was conducted in the study. Based on table 6, both Trace Statistics and Max-eigen Statistics have a p-value of less than 5%. These conditions indicate the existence of cointegration between the variables used in the study. Therefore, the VECM model is suitable for use because the available data has stationary characteristics at first differentiation with cointegration between variables.

Table 6. Johansen Cointegration Test Results

Trace Statistics	Critical Value	Prob.**	Max-Eigen Statistics	Critical Value	Prob.**
81.4014	47.8561	0.0000*	42.0525	27.5843	0.0004*
39.3489	29.7971	0.0030*	24.5415	21.1316	0.0159*
14.8074	15.4947	0.0633	12.5639	14.2646	0.0912
2.24346	3.8415	0.1342	2.2435	3.8415	0.1342

Source: Eviews 12 output (processed).
Note: alpha=5%

Granger Causality Test

The following step is the Granger causality test, with the null hypothesis being that variable X has no effect on variable Y, after the cointegration test is performed and the findings demonstrate that there is cointegration. The purpose of this test is to ascertain the direction of the relationship between CO_2 emissions, GDP, energy consumption, and forest area. H0 is rejected if the p-value is less than the chosen significance level or if the F-statistic is higher than the crucial value.

Table 7. Granger Causality Test Result

Null Hypothesis	F-statistic	Prob.
GDP does not Granger Cause FA	16.479	**2.E-05**
FA does not Granger Cause GDP	0.502	0.611
LNCO2E does not Grange Cause FA	0.123	0.884
FA does not Grange Cause LNCO2E	1.870	0.174
LNEC does not Grange Cause FA	0.187	0.830
FA does not Grange Cause LNEC	2.366	0.113
LNCO2E does not Grange Cause GDP	9.430	**0.000**
GDP does not Grange Cause LNCO2E	0.180	0.835
LNEC does not Grange Cause GDP	1.380	0.269

GDP does not Grange Cause LNEC	1.884	0.172
LNEC does not Grange Cause LNCO2E	1.025	0.372
LNCO2E does not Grange Cause LNEC	0.304	0.740

Source: Eviews 12 Output (processed)

In table 7, the results show that the probability value of GDP against FA is smaller than 5%. This means rejecting the null hypothesis. Meanwhile, the probability value of FA on GDP is greater than 5%. This means that it fails to reject the null hypothesis. Thus, the causality relationship between GDP and FA has a one-way relationship pattern where GDP affects FA. The same results are obtained in the results of the LNCO2E Granger causality test on GDP, which shows a probability value smaller than 5%. This means rejecting the null hypothesis. Meanwhile, the probability value of GDP on LNCO2E is greater than 5%. This means that it fails to reject the null hypothesis. Thus, the causality relationship between LNCO2E and GDP has a one-way relationship pattern where CO2E affects GDP.

The Granger causality test results of LNCO2E to FA and FA to LNCO2E show a probability value greater than 5%. This means that it fails to reject the null hypothesis. Thus, the LNCO2E and FA variables do not influence each other. This is similar to the Granger causality test results of LNEC on FA and FA on LNEC. The results show a probability value greater than 5%, which means that it fails to reject the null hypothesis. Thus, the LNEC and FA variables do not influence each other.

The Granger causality test results of LNEC to GDP and GDP to LNEC show a probability value greater than 5%, which means that it fails to reject the null hypothesis. Thus, the GDP and LNEC variables do not influence each other. The same thing happens in the Granger causality test of LNEC to LNCO2E and LNCO2E to LNEC. The results show a probability value greater than 5%, which means that it fails to reject the null hypothesis. Thus, the LNEC and LNCO2E variables do not influence each other.

Vector Error Correction Model (VECM)

Based on the previous stages, the data used has stationary characteristics at the first differentiation and cointegration between variables. In addition, the optimal lag length of 2 was also obtained in the VAR model stability test. Therefore, to see the long and short-term relationship for CO_2, a VECM model with a lag length of 2 is used. The following presents the VECM model for CO_2 emissions.

$$\Delta CO2E_t = -1{,}1781CO2E_{t-1} + 0{,}1464FA_{t-1} - 0.0237GDP_{t-1} + 4.6419EC_{t-1} - 77.523 + 0.1464\Delta CO2E_{t-1} - 0.1055\Delta CO2E_{t-2} + 0.1280\Delta FA_{t-1} - 0.0178\Delta FA_{t-2} - 0.0620\Delta GDP_{t-1} - 0.0319\Delta GDP_{t-2} + 5.1039EC_{t-1} + 0.8897EC_{t-2} - 0.1033 \quad (2)$$

Based on Table 8, in the long term, CO_2 emissions are influenced by forest area and energy consumption. On the other hand, CO_2 emissions are influenced by economic growth and energy consumption in the previous 1-year period in the short term. In addition, the Error

Correction Term (ECT) value in the VECM model for CO_2 emissions is -1.1781, which indicates a significant amount of adjustment speed to reach equilibrium from the short term to the long term with a deviation correction of 1.1781%. This means that there is long-term cointegration in determining CO_2 emissions in Indonesia.

Table 8. VECM Modeling Results for CO_2 Emissions

Long Term			Short Term		
Variable	**Coef.**	**t Stat.**	**Variable**	**Coef.**	**t Stat.**
LNCO2E(-1)	1	-	CointEq1	-1.1781	-2.4373
FA(-1)	0.3046	7.3068*	D(LNCO2E(-1))	0.1464	0.4225
GDP(-1)	-0.0237	-1.2844	D(LNCO2E(-2))	-0.1055	-0.3912
LNEC(-1)	4.6419	6.9156*	D(FA(-1))	0.1280	1.0022
C	-77.523	-	D(FA(-2))	-0.0178	-0.1108
			D(GDP(-1))	-0.0620	-2.0446*
			D(GDP(-2))	-0.0319	-1.0624
			D(LNEC(-1))	5.1039	1.8685*
			D(LNEC(-2))	0.8897	0.3588
			C	-0.1033	-0.8496

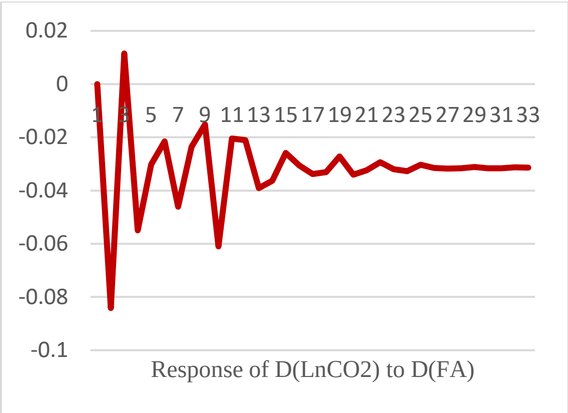
Description: $*\ significance\ at\ the\ level$ 5% $with\ \ t_{table}$= -1,6991
Source: Eviews 12 Output (processed)

In the long term, CO_2 emissions will be 77.52% lower each year due to the constant value of -77.523, assuming that forest area, GDP, and energy consumption are constant. The increase in CO_2 emissions is supported by an increase in forest area and energy consumption in the previous year. Meanwhile, a decrease in CO_2 is supported by an increase in GDP in the previous year. For every 1% increase in forest area, CO_2 emissions will increase by 0.3046%. For every 1% increase in economic growth per capita, CO_2 emissions will decrease by 0.0237%. For every 1% increase in energy consumption, CO_2 emissions will increase by 4.6419%.

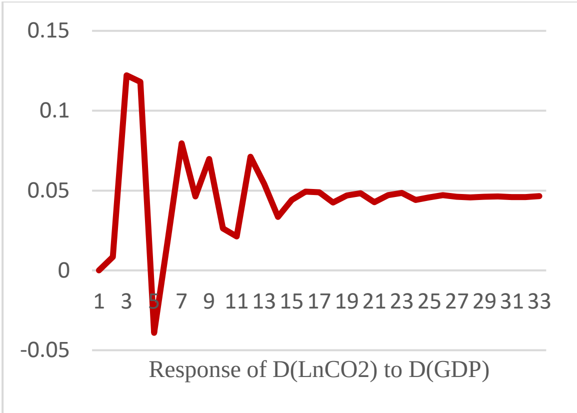
Meanwhile, in the short term, CO_2 emissions will decrease by 0.10% each year due to the constant value of -0.1033, assuming that forest area, GDP, and energy consumption are constant. The increase in CO_2 emissions is supported by an increase in CO_2 emissions and forest area in the previous year, as well as energy consumption in the previous year and two years earlier. Meanwhile, a decrease in CO_2 emissions is supported by an increase in CO_2 emissions and forest area in the previous 2 years, as well as GDP in the previous year and the previous 2 years. For every 1% increase in economic growth in the previous year, CO_2 emissions will decrease by 0.062% in the current year. For every 1% increase in energy consumption in the previous year, CO_2 emissions will increase by 5.1039% in the current year.

Impulse Response Function (IRF)

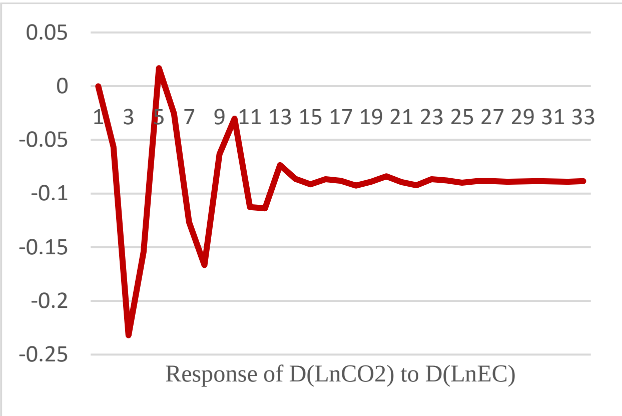
The IRF test is used to investigate the effect of innovation on the variables of GDP, forest area,and energy consumption on CO_2 emissions. The impulse response of CO_2 emissions to 1 standard deviation innovation by GDP, forest area, and energy consumption is shown in Figure 6.



(a) Forest Area Effect on CO_2 Emissions



(b) GDP Growth Effect on CO_2 Emissions



(c) Energy Consumption Effect on CO_2 Emissions

Figure 6. Impulse response results of CO_2 emission

Source: Eviews 12 Output (processed)

Figure (6a) shows the response of CO_2 emissions caused by a shock to the forest area. From the 1st period to the 15th period, the CO_2 response fluctuates, then afterwards the CO_2 response due to forest area starts to stabilize and even constant. From the second period, it can be seen that CO_2 responds negatively to FA with a value of -0.08, while in the third period the response rises to the maximum effect with a value of 0.02. It can be said that the occurrence of shocks to the forest area variable will cause fluctuations in CO_2 emission data around the initial

15 periods. Forest area shocks have a permanent impact on CO_2 emissions because it can be seen that the response forms a new equilibrium below the initial equilibrium. The negative response indicates that when the forest area increases, CO_2 emissions will decrease. Vice versa, if the forest area decreases, CO_2 emissions will increase.

Figure (6b) shows the response of CO_2 emissions caused by a shock to GDP growth. From the first period to the 12th period, the CO_2 response fluctuates, then afterwards the CO_2 response due to GDP growth begins to stabilize and even constant. In the second period, CO_2 responds positively to GDP with a value of 0.13, while in the fifth period the response decreases to the minimum effect with a value of -0.05. It can be said that the occurrence of shocks to the GDP growth variable will cause fluctuations in CO_2 emission data around the initial 12 periods. The CO_2 variable response forms a new equilibrium above the initial equilibrium so that the shock also has a permanent impact on CO_2 emissions. A positive response indicates that when economic growth increases, CO_2 emissions will increase. Conversely, if economic growth decreases, CO_2 emissions will decrease.

Figure (6c) shows the response of CO_2 emissions caused by shocks that occur in energy consumption. From the 1st period to the 13th period, the CO_2 response fluctuates, then afterwards the CO_2 response due to energy consumption begins to stabilize and even constant. In the third period, it can be seen that CO_2 responds negatively to EC with a value of -0.23, while in the fifth period the response rises to the maximum effect with a value of 0.01. It can be said that the occurrence of shocks to the energy consumption variable will cause fluctuations in CO_2 emission data around the initial 13 periods. The existence of shocks to the energy consumption variable has a permanent impact on CO_2 emissions, where the equilibrium after the shock is below the initial equilibrium. The negative response indicates that when energy consumption increases, CO_2 emissions will decrease. Conversely, if energy consumption decreases, CO_2 emissions will increase.

Thus, it can be concluded that an increase in forest area and energy consumption will reduce CO_2 emissions. Conversely, a decrease in both variables will increase CO_2 emissions. It is true that increasing forest area can reduce CO_2 emissions because forests absorb CO_2 in the environment. When many forests are converted into industries, settlements, and others, the CO_2 emissions in the environment cannot be absorbed by plants. Meanwhile, the increase in energy consumption that causes a decrease in CO_2 emissions is different from the research conducted by Jian et al. (2019). There may be other factors that influence the results obtained, so they may be different. In addition, in terms of economic growth, the results show that an increase in economic growth will increase CO_2 emissions. Conversely, a decrease in economic growth will reduce CO_2 emissions. An increase in economic growth will encourage people to buy transportation. In fact, nowadays, everyone has at least one private vehicle. They no longer want to use public transportation because it is considered troublesome, a waste of time, and so on. This will actually increase CO_2 emissions in our environment. The same result was obtained by Espoir et al. (2022) that a country's CO_2 emissions will increase as per capita income increases because fossil fuels support wealth creation.

Forecast Error Decomposition of Variance (FEDV)

Furthermore, to see the contribution of each variable in the VECM model for CO_2 emissions, FEDV analysis can be done. In this research, the contribution of variables in the model will be reviewed in 33 periods, namely from 1990 to 2022.

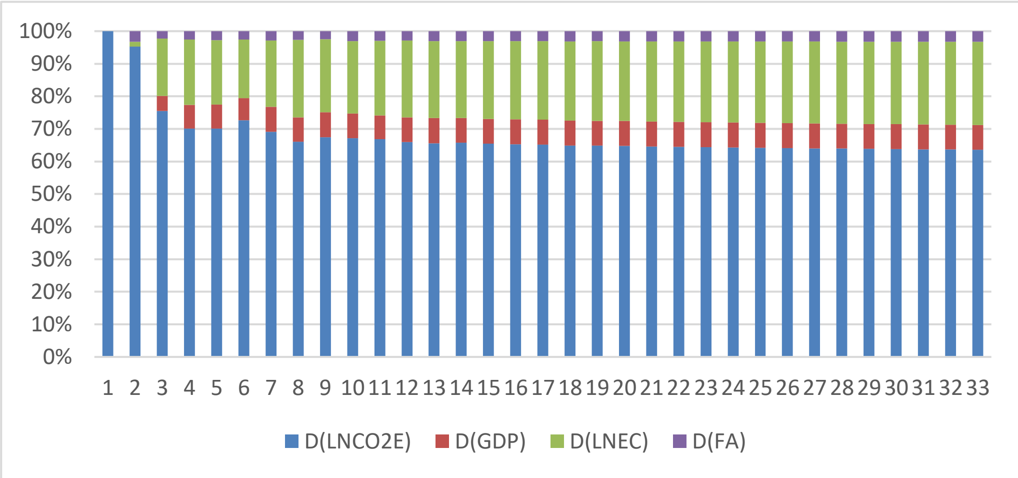


Figure 7. FEDV results on the VECM model of CO_2 emissions in Indonesia
Source: Eviews 12 Output (processed)

Based on Figure 7, in the first period, the behavior of the CO_2 emission variable in Indonesia can only be explained by the variable itself. In other words, other variables have not contributed to influencing the value of the CO_2 emission variable. Different results began to be shown in the following periods. In year 2, the CO_2 emission variable began to be explained significantly by other variables, except for the GDP variable, which had a contribution below 1%. The details of the contribution in that year include a forest area of 3.2% and economic growth of 1.46%. In the next period until the end of the period, the contribution of the forest area variable tends to stabilize, with a contribution of 3.2% in the 33rd year. In contrast to this, the contribution of economic energy consumption and growth to explaining the variation of CO_2 tends to continue to increase as the period increases, which amounted to 7.6% and 25.5% in the 33rd year, even though it had decreased in several periods.

Forecasting

Before forecasting using the VECM model, it is necessary to test the feasibility of the model used. The model feasibility test can be used to determine if the model used fulfills three classical assumptions for the residual value, namely non-autocorrelation, homoscedasticity, and normality.

Autocorrelation Test

$$H_0: nonautocorrelation$$
$$H_0: autocorrelation$$

Conclusion: Reject H_0 when p-value < 0.05

Heteroscedasticity Test

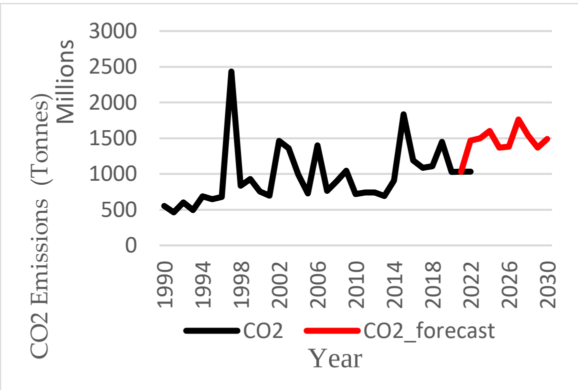
$$H_0: homoskedastic$$
$$H_0: heteroskedastic$$
Conclusion: Reject H_0 when p-value < 0.05

Normality Test

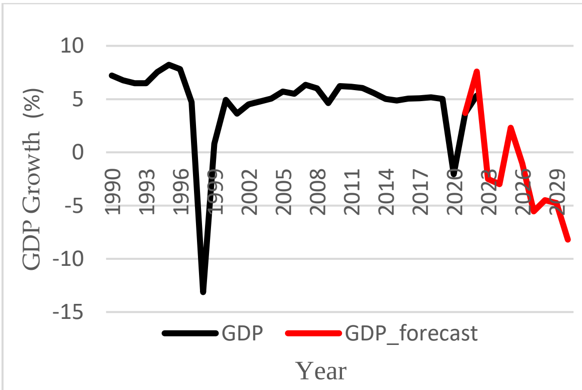
$$H_0: Normally\ Distributed$$
$$H_0: Not\ Normally\ Distributed$$
Conclusion: Reject H_0 when p-value < 0.05

From the results of testing the model obtained using the Eviews 12 software, it is concluded that it fails to reject H0 for the three classical assumptions used. Thus, the model used is feasible, or the model is appropriate for estimation.

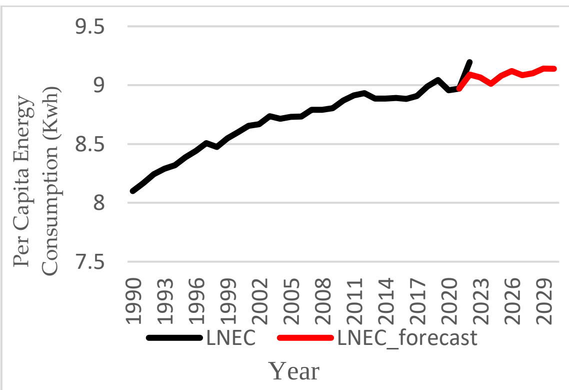
In Figure (8a), it can be seen that the pattern of CO_2 emission data from 1990–2030 in Indonesia fluctuates greatly with a trend that tends to increase. The prediction results of CO_2 emissions in Indonesia from 2024 to 2030 show an upward trend pattern with fluctuations up and down, so it can be said that CO_2 emissions in Indonesia continue to increase until 2030, even though there are different values in each year. Meanwhile, figures (8c) energy consumption and (8d) forest area show the same prediction results as the pattern of previous years, namely experiencing a continuous increase for energy consumption and a continuous decrease for forest area in Indonesia until 2030. Then, in Figure (8b), GDP growth has a fluctuating pattern until 2030 and has decreased.

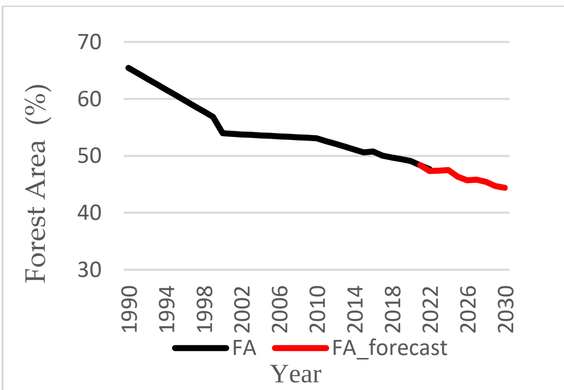


(a)



(b)





(c) (d)

Figure 8. VECM model forecasting results (a) CO_2 emissions, (b) percentage of GDP growth, (c) per capita energy consumption, (d) forest area in Indonesia in 2024-2030 (Eviews 12, processed).

From the forecasting results, several important points can be recognized such as:

1. It is predicted that until 2030, CO_2 emissions in Indonesia will increase.
2. It is predicted that until 2030, the percentage of GDP growth in Indonesia will decrease.
3. It is predicted that until 2030, energy consumption per capita in Indonesia will continue to increase.
4. It is predicted that until 2030, the area of forest in Indonesia will continue to decrease.

CONCLUSION

Numerous significant findings emerged from studies pertaining to the variables of CO_2, energy consumption, forest area, and economic growth over the years 1990–2022. The analysis of the study's data for the years 1990–2022 in Indonesia shows that the reverse curve pattern predicted by the EKC hypothesis was not observed when examining the association between CO_2 emissions and GDP growth as a percentage. The findings of the VECM modeling then show that, in contrast to economic expansion, which only has a short-term impact on CO_2 emissions, the forest area variable influences CO_2 emissions over the long termThe energy consumption variable, in contrast to the other two, has an impact on CO_2 emissions over the long run. The Granger test results then demonstrate that the GDP has a one-way effect on the area of forests. The link between CO_2 and GDP is hence unidirectional and only goes one way. This suggests that adjustments to the GDP growth percentage will result in a corresponding decrease to Indonesia's percentage of forest area. There is a growing possibility of a decline in the amount of forest land because rising GDP also raises the value of producing goods and services. Then, based on the forecasting results using the VECM approach, it can be concluded that Indonesia cannot achieve the SDGs related to climate change by 2030 because the country's CO_2 emissions are expected to continue rising and its forest area to decline.

As a result, this research yields a number of policy recommendations that Indonesia should implement. First and foremost, atmospheric dangers require careful consideration and management. The Indonesian government in particular needs to start planning and implementing measures to cut CO_2 emissions by using alternative energy sources like power plants, hydropower plants, solar power plants, biogas fuel made from animal waste, and sustainably supported environmentally friendly technologies. It is envisaged that this will enable the government to implement ecologically responsible development. Second, it is advised that the Indonesian government work to raise standards of education or to instill a love of the environment and a yard full of trees in all parties. Next, restore the damaged woods to improve Indonesia's forest cover and lower the country's rate of environmental degradation. Third, make sure that the law is vigorously enforced so that negligent people face harsh consequences. For example, irresponsible garbage disposal by factories, illicit tree-cutting, fossil fuel stockpiling, and so forth. In order to help lower CO_2 emissions, it is necessary to update legislation to increase energy effectiveness and implement energy management alternatives across the country by making green energy more accessible. Policymakers are advised to enact laws that promote the use of ecologically friendly appliances, machines, cars, and utilities in order to limit environmental degradation over the long run.

Moreover, there are undoubtedly flaws and inconsistencies in the study that has been done. Thus, in order to reduce the projected error rate of the estimated figure, researchers propose a number of recommendations for future research, including carrying out additional investigation into variables that may also contribute to the rise in CO_2 emissions. Then, in an effort to improve the description of the pattern of the relationship between economic growth and environmental harm, more observations must be gathered for research employing the Kuznet hypothesis. Lastly, employ additional pertinent predicting or estimating techniques so that the outcomes can be contrasted with previous study.

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