Jurnal Pertanian Agros Vol.26 No.1, Januari 2024: 4848-4865

THE EFFECT OF INDUSTRIAL VALUE ADDED, ENERGY CONSUMPTION, FOOD CROP PRODUCTION, AND AIR TEMPERATURE ON GREENHOUSE GAS EMISSIONS IN INDONESIA: A TIME SERIES ANALYSIS APPROACH

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ABSTRACT

Air quality and global warming, which cause climate change and affect many aspects of human life, have become important topics in recent years. The objective of this study is to assess the influence of greenhouse gas emissions on industrial added value, energy consumption, food crop production, and air temperature in Indonesia. The period covered is 1990–2022. The Granger causality test and the vector error correction model are employed to establish the causal connection between the variables, and the unit root test is used to confirm the data's stationarity. The study's findings demonstrate that, over the long run, greenhouse gas emissions in Indonesia are known to be positively impacted by energy use, crop output, and temperature. Short-term analysis shows that air temperature has a negative impact on greenhouse gas emissions in Indonesia, but the added value of industry, energy consumption, and food crop output have a favorable impact. In light of the study's findings, it is anticipated to serve as the foundation for the Indonesian government's deliberations when implementing the required policies to lower greenhouse gas emissions, while still paying attention to the added value in the industrial sector as well as a basis for determining other policies. In addition, controlling fossil energy consumption must also be actively carried out by intensifying the use of renewable fuels.

Keywords: Greenhouse gases, Industrial value added, Energy consumption, Food crop production, Air temperature, VECM

INTRODUCTION

Indonesia is part of the world's *largest carbon emitters* or greenhouse gas emitters. A number of gases that result from global warming and are released into the atmosphere, which then cause the greenhouse effect are called Greenhouse Gases or GHGs. In some cases, water vapor is classified as a GHG, but water is considered a natural element, so it is not classified as a trigger of climate change due to global warming. The occurrence of the greenhouse effect may result from heightened discharges of gases like carbon dioxide (CO2), methane (CH4), nitrous oxide (N2O), chlorofluorocarbons (CFCs), and similar substances. Greenhouse gas emissions cause energy emitted by the sun to be trapped within the earth's atmosphere. Along with retaining some of the heat energy reflected by the earth and allowing solar radiation to penetrate the atmosphere, some of these gases act like the roof of a greenhouse, causing the earth to warm. Since the end of the 19th century, the earth's surface has experienced a temperature increase of about 0.6 degrees Celsius. In 2000, combined ocean and land temperatures were 0.29 degrees Celsius above the average daily temperature for the period 1961 to 1990 (Godish, 2004; Q. Wang & Wang, 2019; X. Wang et al., 2016). However, emissions that support global warming are not limited to carbon emissions, but also come from elements such as fluorine (F), sodium (N) and so on. Therefore, the term "greenhouse gas emission exposure" is used in some studies (Prado-Lorenzo et al., 2009).

Greenhouse gases are gases that can provide a greenhouse effect found in the earth's

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atmosphere both sourced from human activities and formed naturally (Kartiasih & Setiawan, 2020; Pribadi & Kartiasih, 2020). Greenhouse gases absorb and emit infrared radiation or longwave radiation. In the lower atmosphere near the surface of the earth, longwave radiation emitted by greenhouse gases is absorbed and causes a warming effect known as the greenhouse effect. Six categories of greenhouse gases are recognized by the United Nations Framework Convention on Climate Change (UNFCCC): carbon dioxide (CO2), methane (CH4), nitrogen oxides (N2O), hydrofluorocarbons (HFCs), perfluorocarbons (PFCs), and sulfur hexafluoride (SF6). According to Murawska & Goryńska-Goldmann, (2023), nitrous oxide, carbon dioxide (CO2), and methane (CH4) are the long-term anthropogenic greenhouse gases that have the biggest effects on climate change. According to the Intergovernmental Panel on Climate Change (IPCC), the categories of greenhouse gas emissions are classified into six sources, which encompass energy, industrial processes, products, and the use of solvents, as well as agriculture, forestry, aquaculture, and waste. Global climate change, often referred to as global warming, pertains to a sustained rise in the Earth's surface average temperature over an extended period. In a similar sense, global warming is a condition characterized by increasing average temperatures on the earth's surface and ocean and is expected to continue (Pinontoan et al., 2022). Global warming conditions occur in all countries of the world, including Indonesia. Indonesia is ranked third in terms of high climate risk (World Bank Group, & Asian Development Bank, 2021). The emission of greenhouse gases contributing to global warming is a major factor behind carbon dioxide emissions globally, and Indonesia is no different. The consequences of global warming encompass various effects on the environment, economy, and human well-being (Abbass et al., 2022; Li et al., 2019).

The emissions of carbon dioxide and greenhouse gases represent contributing factors to the onset of climate change and global warming. This is in accordance with Thompson's (1992) explanation because CO2 affects the lifetime of other greenhouse gases such as methane (CH4) because it acts as a major sink for tropospheric hydroxyl radicals. According to the World Resource Institute (2018), Indonesia is the 8th largest carbon emitter. Emissions of CO2 have increased over the years, Dincer et. al (2013) in their book explained that CO2 emissions have increased from 141 million tons to 327 million tons from 1990 to 2010. The carbon footprint is defined as carbon dioxide (CO2) emissions in direct and indirect human activities (Chambers et al., 2007; Hashimoto et al., 2016; Kenny & Gray, 2009), measured in tons. In addition to the use of fossil fuels, the use of electronic devices is also a contributor to the release of carbon emissions. The *Journal of Cleaner Production* explains that the contribution of ICT (Information and Computer Technology) to the global carbon footprint is expected to increase from 1% in 2007, rising to 3.5% in 2020, and projected to reach 14% by 2040. CO gas emissions2 can arise from irresponsible human and economic activities, such as threats to the global ecosystem and significant impacts (Antonakakis et al., 2017; Harris & Roach, 2021; Ziabakhsh-Ganji & Kooi, 2014).

The energy sector (including gases released into the atmosphere during the combustion of solid, liquid, and gaseous fuels as well as gas leaks), transportation and industry (including emissions from industrial processes like production), agriculture (including emissions related to food production and soil fertilization, as well as greenhouse gas emissions and disposal from land conversions like converting forests into agricultural land), and landfills (including emissions from the process of disposing of solid and liquid waste that occurs in landfills) are the main sources of anthropogenic gas emissions. According to Murawska & Goryńska-Goldmann, (2023) research, industry and agriculture play a major role in contributing to greenhouse gas emissions in European countries. In developing countries like Indonesia, where agriculture is the main industry and source of wealth (Kartiasih et al., 2022; Kartiasih & Setiawan, 2019; Harum et al., 2023; Wardana et al., 2023), emission reduction strategies like utilizing technology and innovation in the agricultural sector can greatly help achieve the SDGs. Agriculture accounts for 10.3% of total greenhouse gas emissions, while industry accounts for 9.1%. The industrial sector emits more carbon dioxide (CO2) than agricultural, whereas agriculture emits the most methane (CH4) and nitrous oxide (N2O).

Emissions from food crops and livestock activities in the world continued to increase throughout the period 2000 to 2018. Agricultural activities derived from food crops produce emissions of non-gases. Methane and nitrous oxide are two examples. Both are very potent greenhouse gases with a total emission of 5.3. Indonesia was the fifth-largest emitter of CO2eq in 2018, accounting for almost 200Mt CO_2eq. Indonesia ranked first in terms of agriculture-related land use emissions, with about 730Mt CO2eq created primarily from peatland degradation processes (drainage and fire) associated with the growth of the food crop oil palm (Demetrio et al., 2021; Kapica et al., 2015; Zhou et al., 2023). The three agriculture-related greenhouse gases CO2, CH4, and CO2 have different heat trapping efficiency and atmospheric turnover rates. Nitrogen (N) fertilizers are widely used around the world to meet the world population's expanding needs for food, fiber, and fuel (Snyder et al., 2009). Emissions resulting from activities both before and after production, such as the manufacturing of fertilizers, transportation of food, processing, retail sales, and waste disposal, contribute to the magnification of the impact (Tubiello et al., 2021).

This aligns with the results obtained from a study undertaken by Tongwane et al, (2016), which found that food crops contribute to greenhouse emissions, with each crop contributing differently. Cereal crop production accounts for 68% of greenhouse gas emissions, with synthetic fertilizers, crop residues, and lime accounting for 61%, 14%, and 25% of emissions, respectively. Other field crops supplied 48%, 17%, and 35%, respectively, owing to synthetic fertilizers, agricultural residues, and lime.

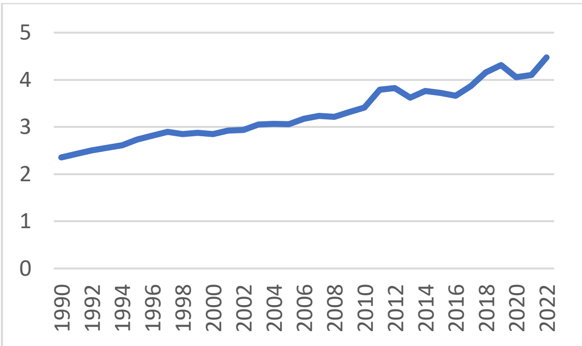

Figure 1. Greenhouse Gas Emissions Data
Source: Publications Office of the European Union (2022)

Based on energy consumption data from the World Bank, it can be seen that energy consumption in Indonesia reached 2714.92 billion in 2022. According to the graph, there has been a rise in gas emissions over the preceding year. Based on the chart, energy consumption in Indonesia tends to rise and reach the highest level in 2022. Based on *Climate Watch* data in 2017, energy contributed the most in contributing to greenhouse gas emissions. The sector can produce 36.44 gigatons of carbon dioxide (Gt CO2e). Human-induced climate change is primarily attributed to energy consumption, particularly from coal, oil, and natural gas, which contributes to over 80% of anthropogenic greenhouse gas emissions. (Akpan & Akpan, 2012; Dogan & Seker, 2016).

According to Rehman et al, (2021), forestry yield, the production of food crops and animals, population growth, precipitation, and temperature collectively contribute positively to the emission of greenhouse gases, notably carbon dioxide. This is consistent with the findings of Nam et al., (2010), who discovered that PM emissions rise with decreasing temperatures. Based on Indonesia's temperature data contained in the World Bank, it can be seen that Indonesia's temperature decreased in 2022. The decrease in temperature is in line with the increase in PM emissions (Nam et al., 2010a). The impact of greenhouses can be useful to provide stability to the earth's temperature. Excessive amounts of greenhouse gases can have a less positive impact, such as an increase in global temperature so that it can have an impact on melting icebergs in the North and South Poles so that sea levels will rise by about 7 meters, islands that have low altitudes (usually small islands) will sink, and relatively high islands (usually large islands) will experience coastal shrinkage causing storms and tsunamis (Muliana et al., 2021).

Indonesia was chosen as the location for this study because the Indonesian government's plan aims to reduce carbon dioxide emissions from all sectors by 29 percent by 2030 or up to 41 percent with foreign funding. Regarding the 41 percent reduction target, the government hopes to establish coordination with developed countries that have high carbon emissions through a "carbon trading" mechanism (Ministry of Environment and Forestry). This study uses greenhouse gas data as the dependent variable while the independent variable uses industrial value-added data, energy consumption, food crop production value, and temperature data. The research can establish the connection between each independent variable and the dependent variable. Based on research conducted by Zhang & Ren, (2011), industrial-added value has a unidirectional relationship with greenhouse gas emissions, especially CO2. This shows that changes in industrial structure reduce emissions. According to the journal, the way to reduce emissions is to adjust the industry. Based on research conducted by Yusuf et al, (2020), energy consumption does not have a significant positive impact on greenhouse gases, especially mostly on CO2 and CH4. According to Kabange et al, (2023), food crop production can increase the impact of climate change by increasing greenhouse gas emissions. According to study conducted by (Nam et al., 2010b; Si et al., 2021a), PM emissions rise when temperature decreases.

This study has multiple goals, including presenting an overview of greenhouse gas emissions and investigating variables to anticipate greenhouse gas emissions in Indonesia. In the research we conducted, there is an element of novelty, namely the variables of industrial added value, energy consumption, food crop production value, and temperature. The previous study that became a reference for our study, was conducted by Rehman et al, (2021) Using population increase, climate change, forestry, animal husbandry, and crop production as factors. By conducting this research, it can provide benefits both for Indonesia and other researchers. The first benefit is that conducting this research can contribute by providing an overview of the condition of industrial added value, energy consumption, and food production on greenhouse gas emissions so that it can help in making policies related to the economy and the environment. With the right policymaker base, it can produce policies that are more focused, specific, and results-oriented. The second advantage can assist authorities in developing measures to reduce greenhouse gas emissions in Indonesia based on independently studied variables. The third benefit is that this research can help Indonesia design a movement for energy consumption that is more friendly to the environment. The fourth benefit can help Indonesia in carrying out appropriate mitigation to reduce the impact due to temperature fluctuations. The fifth benefit can be a reference basis for other researchers to make research similar to the latest innovations based on the evaluation of this study. A good understanding of the added value of industry, energy consumption, food crop production, and air temperature on greenhouse gas emissions can make a significant contribution to achieving sustainable development in Indonesia. This study used the VECM method. Initially introduced by Engle & Grangeri in 1987, the technique of the vector error correction model is applied to rectify short-term discrepancies within a long-term context. Thus, VECM can be utilized to examine the interrelationships in the short and long term of a time series data. VECM is a *Vector Auto Regression* (VAR) analysis intended for data that is not stationary and has a cointegration relationship, in other words, VECM is a restricted VAR (Hutabarat, 2017). It can be concluded that the VECM method is different from VAR, the difference lies in its use. VECM is used in modeling cointegrated *time series* data. Variables in the VECM model must be stationary at first differentiation.

DATA AND METHODOLOGY

The data used in this study covers an annual period from 1990 to 2022, totaling 32 observations. The main dependent variable in this study is greenhouse gas emissions and the four independent variables used are industrial value added, food crop production, renewable energy consumption, and unemployment rate. Four data sources were used, namely: (i) Worldbank for industrial value added and air temperature variables, (ii) Our World in Data for renewable energy consumption, (iii) OECD for food crop production variables, and (iv) Publications Office of the European Union for greenhouse gas emissions variables.

Stationary Test (Unit Root Test)

This test is important in the analysis of time series data because if there is a nonstationary data and estimation is done with the data, the estimate will be very high ($R^2 >$ 0.9). However, in reality, the relationship between the variables does not exist, resulting in a spurious regression. To test the stationarity of the data, we can use the unit root test, with the Augmented Dickey-Fuller (ADF) test statistic as the method. Here is the equation:

$$\Delta Y_t = \gamma + \delta t + \rho Y_{t-1} + \sum_j^k \phi_j \, \Delta Y_{t-j} + e_t$$

With $\Delta Y_t = Y_t - Y_{t-1}$ and $\rho = a - 1$

The hypothesis used is $H0 : \rho = 0$ (there are unit roots). At the confidence level $(1 - \alpha)100\%$, H_0 is rejected if the ADF statistic is less than the critical value at time α or $p - value$ is smaller than the confidence level α. Rejection H_0 indicates that the data is stationary.

Determination of Optimal Lag Var

$$AIC(p) = \log\det\left(\sum_u^{\wedge}(p)\right) + \left(2_p k^2\right)/T$$

$$SC(p) = \log\det\left(\sum_u^{\wedge}(p)\right) + (\log(T)\, pk^2)/T$$

With $\sum_u^{\wedge}(p) = T^{-1}\sum_{t=1}^{T} \hat{u}_t \hat{u}_t$, where T represent the sample size and k is the number of endogenous variables used. The lag value p is determined as the P* value that minimizes the information criterion within the observed interval of 1 to $p\ max$ observed. Furthermore, the optimum lag is selected through information criteria based on the smallest AIC and SC values.

Table 1. Research Variables

Variables	Description	Measurement Unit	Data Source
GHG	Greenhouse gas emissions (including CO2, CH4, N2O, HFCs, PFCs, SF6)	tCO_2eq/capita/year	Publications Office of the European Union
Industry	Industry value added	US$	World Bank
Energy	Energy consumption	TWh	Our World in Data
Crop	Food crop production	tons/hectar	OECD
Temp	Air temperature	ºC	World Bank

Source: Publications Office of the EU, World Bank, Our World in Data, and OECD

Johansen Cointegration Test

It can be modeled as follows:

$$y_t = A_t y_{t-1} + \cdots + A_p y_{t-p} + Bx_t + e_t$$

With yt is a vector with k non-stationary variable, xt is a vector with d deterministic variables, et is the error vector. For hypothesis testing we can use the following Trace test:

$$LR_{tr}(r|k) = -T\sum_{i=r+1}^{k}\log(1-\lambda_i)$$

It can also use the eigenvalue Maximum Test, as follows:

$$LR_{max}(r|r+1) = -T\log\left(1-\lambda_{y+1}\right)$$
$$= LR_{tr}(r|k) - LR_{tr}(r+1|k)$$

For $r = 0,1, \ldots, k-1$, with the hypothesis used is H_0: There are r cointegration equation. At the confidence level $(1-\alpha)100\%$, H_0 is accepted When the trace test and max eigenvalue test are less than the critical value when α or $p-value$ more than the confidence level α.

Vector Error Correction Model

This research uses the Vector Error Correction Model (VECM) to study the long-run and short-run dynamic relationships between greenhouse gas emissions and industrial value added, energy consumption, crop production, and air temperature. "Pseudo-regression" will be generated by direct regression because most time series are non-static (Jia et al., 2020; Jian et al., 2019). Therefore, the idea of cointegration, which indicates a stable relationship between variables over a long period of time, is proposed. (Engle & Grangeri, 1987). Furthermore, multivariate model analysis with a unit root was discovered (Sims et al., 1990). From this analysis, the VECM model became the proposed formal model. The VECM model is widely used to study the relationship between cointegrating variables and long-run and short-run equilibrium (Kartiasih et al., 2012; Ningsih & Kartiasih, 2019). If the variables in this study are cointegrated, the VECM model equation is written as follows:

$$\Delta GHG_t = \varphi_1 + \sum_{i=1}^{n}\alpha_{1i}\ \Delta GHG_{t-i} + \sum_{j=1}^{n}\beta_{1i}\ \Delta\ln industry_{t-j} + \sum_{k=1}^{n}\gamma_{1i}\ \Delta\ln Energy_{t-k} + \sum_{q=1}^{n}\delta_{1i}\ \Delta Crop_{t-q} + \sum_{r=1}^{n}\theta_{1i}\ \Delta Temp_{r-1} + \xi_1\, ECT_{t-1} + \mu_{1t} \quad (1)$$

$$\Delta \ln Industry_t = \varphi_2 + \sum_{i=1}^{n}\alpha_{2i}\ \Delta\ln Industry_{t-i} + \sum_{j=1}^{n}\beta_{2j}\ \Delta GHG_{t-j} + \sum_{k=1}^{n}\gamma_{2i}\ \Delta\ln Energy_{t-k} + \sum_{q=1}^{n}\delta_{2i}\ \Delta Crop_{t-q} + \sum_{r=1}^{n}\theta_{2i}\ \Delta Temp_{r-1} + \xi_2\, ECT_{t-1} + \mu_{2t} \quad (2)$$

$$\Delta lnEnergy_t = \varphi_3 + \sum_{i=1}^{n}\alpha_{3i}\ \Delta\ln energy_{t-i} + \sum_{j=1}^{n}\beta_{3j}\ \Delta GHG_{t-j} + \sum_{k=1}^{n}\gamma_{3k}\ \Delta Industry_{t-k} + \sum_{q=1}^{n}\delta_{3q}\ \Delta Crop_{t-q} + \sum_{r=1}^{n}\theta_{3r}\ \Delta Temp_{r-1} + \xi_3\, ECT_{t-1} + \mu_{3t} \quad (3)$$

$$\Delta Crop_t = \varphi_4 + \sum_{i=1}^{n}\alpha_{4i}\ \Delta Crop_{t-i} + \sum_{j=1}^{n}\beta_{4j}\ \Delta GHG_{t-j} + \sum_{k=1}^{n}\gamma_{4k}\ \Delta Industry_{t-k} + \sum_{q=1}^{n}\delta_{4q}\ \Delta\ln Energy_{t-q} + \sum_{r=1}^{n}\theta_{4r}\ \Delta Temp_{r-1} + \xi_4\, ECT_{t-1} + \mu_{4t} \quad (4)$$

$$\Delta Temp_t = \varphi_5 + \sum_{i=1}^{n}\alpha_{5i}\ \Delta Temp_{t-i} + \sum_{j=1}^{n}\beta_{5j}\ \Delta GHG_{t-j} + \sum_{k=1}^{n}\gamma_{5k}\ \Delta Industry_{t-k} + \sum_{q=1}^{n}\delta_{5q}\ \Delta\ln Energy_{t-q} + \sum_{r=1}^{n}\theta_{5r}\ \Delta Crop_{r-1} + \xi_5\, ECT_{t-1} + \mu_{5t} \quad (5)$$

Granger Causality Test

Causality analysis serves to examine both long-term and short-term causal relationships. In VECM modeling, the assessment of long-term causality involves examining the significance of the Error Correction Term (ECT) coefficient through the Ordinary Least Squares (OLS) method. On the other hand, short-term causality is assessed using the Granger causality test, typically relying on the Wald or chi-square test. The hypotheses involved in this analysis are framed as H_0: No Granger causality relationship exists between the variables.

Variance Decomposition

Variance decomposition involves breaking down a variable into components within a VAR model. The analysis seeks to quantify the influence of a variable on others as a percentage, enabling predictions of which variables need adjustment to attain a specific value. Typically, the primary contributor to changes in a variable is the variable itself (Hawari & Kartiasih, 2017; Juliansyah et al., 2022; Pertiwi et al., 2023).

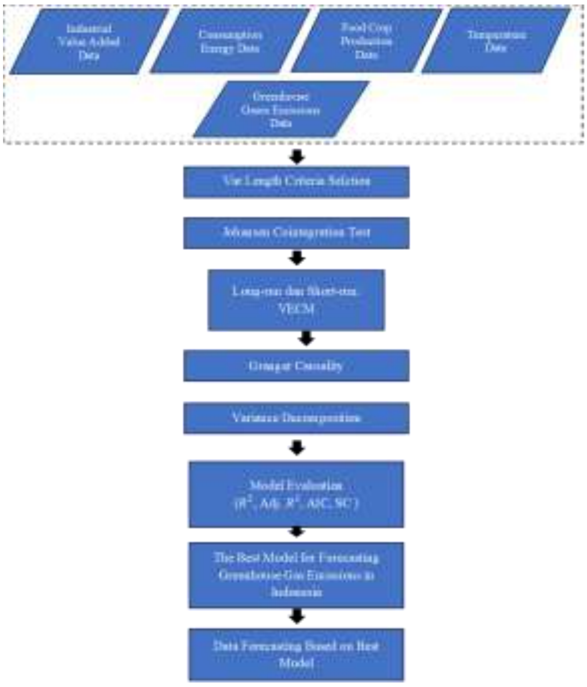

Figure 2. Research Flow

RESULT AND DISCUSSION

Overview of Greenhouse Gas Emissions in Indonesia 1990-2022

During the period 1990 to 2022, there was an increasing trend in greenhouse gas emissions in Indonesia. This increase in greenhouse gas emissions should be of particular concern to all parties because greenhouse gases are one of the triggers for increased global warming. In addition, industrial value added in Indonesia during the same period also had an increasing trend. Industrial value added illustrates the effective and efficient production activities of an industry. The rise in industrial value added indicates Indonesia's fast industrialization, but it also contributes to greenhouse gas emissions. The industrial sector is closely related to energy consumption because most industrial activities are carried out using energy. Energy consumption has an increasing trend from 1990 to 2022, which shows that the industrialization process and technological development are highly dependent on using energy, especially fossil energy. The food crop production sector also has an increasing trend. Air temperature in Indonesia in the period 1990-2022 tends not to show a clear trend characterized by the development of temperature that fluctuates every year.

Figure 8 shows that the greenhouse gas emissions variable has a strong correlation with the variables of industrial added value, energy consumption, food crop production and air temperature. This indicates the potential for a causal relationship between these variables, thus emphasizing the need for a comprehensive in-depth analysis. Based on the description of the development and correlation between the variables used, it can be assumed that there is a causal relationship between greenhouse gas emissions and industrial added value, energy consumption, food crop production, and air temperature. This description is the basis for analysis to investigate more deeply the influence of independent variables on greenhouse gas emissions in Indonesia.

Stationarity Testing

One of the conditions that must be met in analyzing time series data is stationarity. To test the stationarity of variables, this study uses the Augmented Dickey-Fuller (ADF) unit root test. The unit root test was carried out at level and first difference to determine the appropriate data analysis method. If the data is stationary at level, the analysis method used is VAR, whereas if it is stationary at first difference using VECM.

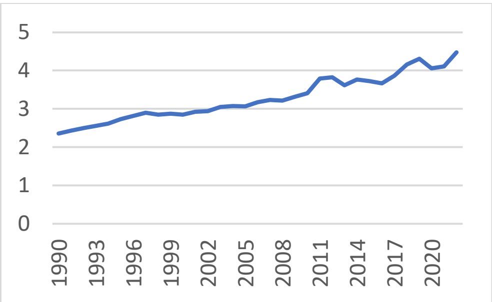

Figure 3. Growth of Greenhouse Gas Emissions
Source: Publications Office of the EU (2022)

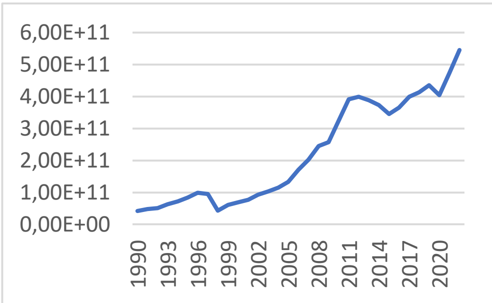

Figure 4. Growth of Industry Value Added
Source: World Bank (2022)

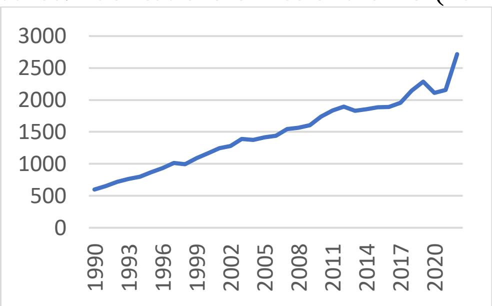

Figure 5. Growth of Energy Consumption
Source: Our World in Data (2022)

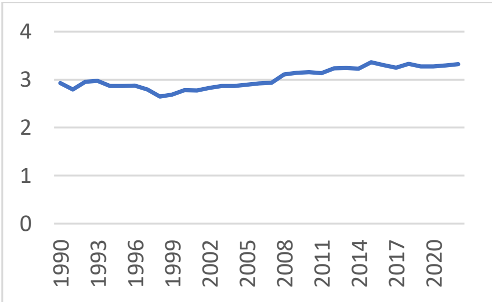

Figure 6. Growth of Food Crop Production
Source: OECD (2022)

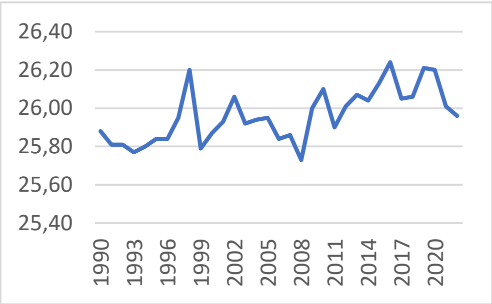

Figure 7. Growth of Air Temperature
Source: World Bank (2022)

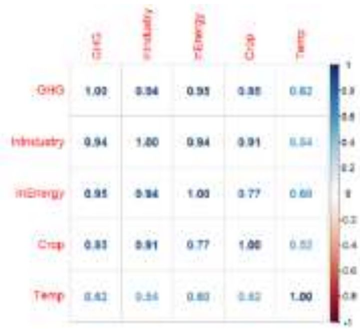

Figure 8. Correlation between the Variables
Source: Data Processed

Table 2. The result of unit root test

Variabel	ADF test statistic (Prob.)	
	Level	First difference
GHG	0.9837	0.0000
lnIndustry	0.7867	0.0001
lnEnergy	0.1345	0.0007
Crop	0.8782	0.0000
Temp	0.0374	0.0000

Note: *MacKinnon (1996) one-sided p-values.

The unit root test results at level show non-stationary conditions, with a p-value above the 5% significance level. In contrast, when taking first differences, the p values for all variables exceeded the 5% significance level, indicating that stationarity was achieved through initial differences for all variables. Therefore, it can be concluded that the order of integration of all the variables under consideration is 1, denoted by I (1).

Determination of Optimal Lag

The identification of the optimal lag length employed in data analysis is evident in the table presenting the criteria for selecting the lag order in VAR (Vector Autoregressive) modeling.

Table 3 shows the results of the VAR lag selection values based on several metrics. The metrics used are LogL, Likelihood Ratio (LR), Final Prediction Error (FPE), Akaike Information Criterion (AIC), Schwarz Information Criterion (SC), and Hannan-Quinn Information Criterion (HQ). The results in the table show that lag 1 is the optimal lag length. Therefore, this study uses lag 1 as the optimum lag applied to the model equation and the lag in the cointegration test.

Johansen Cointegration Test

Stationarity testing shows that not all variables are stationary at level, but stationarity for all variables occurs in the first difference so this indicates that the analysis process with the Vector Error Correction Model (VECM) method can be used. However, analysis with VECM can be done if there is cointegration in the data used.

Table 3. VAR lag order selection criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	62.960	NA	0.000	-3.739	-3.508	-3.664
1	193.136*	209.961*	0.000*	-10.525*	-9.137*	-10.073*
2	209.445	21.043	0.000	-9.964	-7.420	-9.135

Note: * indicates lag order selected by the criterion. Source: Data processed

Table 4. Johansen Cointegration Test Results

Hypothesized No. of CE(s)	Trace Statistic			Hypothesized No. of CE(s)	Maximum Eigenvalue Statistic		
	Statistic	0.05 Critical Value	Prob.		Statistic	0.05 Critical Value	Prob.
None *	99.717	88.804	0.007	None	32.14126	38.33101	0.2163
At most 1 *	67.576	63.876	0.024	At most 1	30.43613	32.11832	0.0791
At most 2	37.139	42.915	0.168	At most 2	24.44967	25.82321	0.0751
At most 3	12.690	25.872	0.762	At most 3	9.489361	19.38704	0.6733
At most 4	3.200	12.518	0.852	At most 4	3.200433	12.51798	0.8519

Note: * denotes rejection of the hypothesis at the 0.05 level. Source: Data processed

Table 4 presents the analysis of the cointegration relationship among the variables using the Trace and Maximum Eigenvalue Statistic. The results of the trace statistic test indicate a rejection of the null hypothesis (H_0) at the 5% significance level, signifying the presence of cointegration among the considered variables. In this study, 2 cointegration equations are employed in Vector Error Correction Model (VECM) to explore the long-term relationship between the variables.

Table 5. VECM estimation for long run cointegration equation 1

	Coef.	Std. error	t-stat	p-value
GHG(-1)	1.000			
lnIndustry(-1)	0.000			
lnEnergy(-1)	-6.546	-1.273	-5.143	0.000
Crop(-1)	-4.115	-0.874	-4.708	0.000
Temp(-1)	-1.771	-1.110	-1.596	0.121
@Trend(90)	0.267	-0.065	4.075	
C	97.933			

Source: Data processed

Table 6. VECM estimation for long run cointegration equation 2

	Coef.	Std. error	t-stat	p-value
GHG(-1)	0.000			
lnIndustry(-1)	1.000			
lnEnergy(-1)	-10.225	-1.442	-7.091	0.000
Crop(-1)	-7.082	-0.990	-7.152	0.000
Temp(-1)	-0.316	-1.257	-0.251	0.803
@Trend(90)	0.430	-0.074	5.795	
C	70.395			

Source: Data processed

Table 7. VECM estimation for short run equation

	Coef.	Std. error	t-stat	p-value
CointEq1	-0.588	-0.160	-3.673	0.001
CointEq2	0.539	-0.140	3.860	0.001
D(GHG(-1))	0.290	-0.268	1.083	0.287
D(lnIndustry(-1))	0.054	-0.158	0.340	0.736
D(lnEnergy(-1))	0.579	-0.843	0.687	0.497
D(Crop(-1))	0.861	-0.455	1.892	0.068
D(Temp(-1))	-0.215	-0.227	-0.948	0.351
C	0.012	-0.034	0.350	0.728

Source: Data processed

Estimation of Vector Error Correction Model

Based on the statistical tests that have been carried out, the data used meets the requirements to be analyzed using the VECM method. Therefore, the model estimation obtained is the short run and long run equations with two cointegration equations. Based on Table 8, the model estimation results obtained have R-Squared amounted to 0.443. This result shows that the variables of industrial value added, energy consumption, food crop production, and air temperature are able to explain 44.3% of the variation of greenhouse gas emissions in Indonesia from 1990 to 2022.

Table 8. Model evaluation

R-squared	0.443
Adj. R-squared	0.273
Sum sq. resids	0.295
S.E. equation	0.113
F-statistic	2.612
Log likelihood	28.163
Akaike AIC	-1.301
Schwarz SC	-0.931
Mean dependent	0.066
S.D. dependent	0.133

Source: Data processed

Table 5 displays the results of the Vector Error Correction Model (VECM) estimation. The adjusted coefficient value for cointegration equation 1 is -0.588, and for cointegration equation 2, it is 0.539. The p-values for the vector error correction model on cointegration and for cointegration are both 0.001, suggesting the model's significance at the 5% level. The negative coefficient of the error correction term and the significant p-value of the vector error correction imply that the derived model is well-suited for offering policy recommendations (Rehman et al., 2021). The long-term equation incointegration 1 states that there is a positive effect of energy consumption, food crop production, and air temperature variables on greenhouse gas emissions with coefficient values of -6.546, -4.115, and -1.771, respectively. Meanwhile, cointegration equation 2 also states that energy consumption, food crop production, and temperature negatively affect greenhouse gas emissions with coefficient values of -10.225, -7.082, and -0.316, respectively. The adverse impact of energy consumption and temperature on greenhouse gas emissions, as identified in this study, contradicts the outcomes of prior research conducted by (Chandran et al., 2013) and (Rehman et al., 2021). These studies assert empirical evidence of a one-way relationship between greenhouse gas emissions, particularly CO2, and both energy consumption and temperature. This discrepancy could potentially be attributed to the extensive adoption of renewable energy sources.

In the short-term equation, the results found are that there is a positive influence of the variables of industrial value added, energy consumption, and food crop production on greenhouse gas emissions with coefficient values of 0.054, 0.579, and 0.861, respectively. *P-value* for each variable is 0.287, 0.736, and 0.497. Meanwhile, the negative effect is given by the air temperature variable on greenhouse gas emissions with a coefficient of -0.215 and p-value of 0.351. In this case, food crop production has a major influence on greenhouse gas emissions as indicated by the largest coefficient of the other variables. The production process of food crops requires resources such as nitrogen-containing fertilizers.

Granger Causality

In this study, the Granger causality test was employed to examine the causal relationships among variables, encompassing greenhouse gas emissions, the impact of industrial value-added, energy consumption, food crop production, and air temperature. The outcomes of the Granger causality test calculations are presented in the accompanying table.

Table 9. Granger Causality Test Results

	F	df1	df2	p	Chisq	df	p
GHG <= lnIndustry	0.50	1	26	0.488	0.50	1	0.481
GHG <= lnEnergy	0.14	1	26	0.713	0.14	1	0.710
GHG <= Crop	0.29	1	26	0.594	0.29	1	0.589
GHG <= Temp	0.29	1	26	0.592	0.29	1	0.588
GHG <= ALL	1.04	4	26	0.407	4.14	4	0.387
lnIndustry <= GHG	1.56	1	26	0.223	1.56	1	0.211
lnIndustry <= lnEnergy	6.08	1	26	0.021*	6.08	1	0.014*
lnIndustry <= Crop	4.50	1	26	0.044*	4.50	1	0.034*
lnIndustry <= Temp	0.25	1	26	0.621	0.25	1	0.617
lnIndustry <= ALL	1.65	4	26	0.193	6.59	4	0.159
lnEnergy <= GHG	0.21	1	26	0.649	0.21	1	0.646
lnEnergy <= lnIndustry	0.05	1	26	0.827	0.05	1	0.825
lnEnergy <= Crop	0.05	1	26	0.819	0.05	1	0.817
lnEnergy <= Temp	0.30	1	26	0.591	0.30	1	0.586
lnEnergy <= ALL	0.14	4	26	0.964	0.57	4	0.966
Crop <= GHG	0.35	1	26	0.559	0.35	1	0.554
Crop <= lnIndustry	0.21	1	26	0.653	0.21	1	0.649
Crop <= lnEnergy	0.04	1	26	0.835	0.04	1	0.834
Crop <= Temp	1.32	1	26	0.261	1.32	1	0.250
Crop <= ALL	1.83	4	26	0.153	7.32	4	0.120
Temp <= GHG	0.75	1	26	0.395	0.75	1	0.387
Temp <= lnIndustry	0.07	1	26	0.799	0.07	1	0.797
Temp <= lnEnergy	0.04	1	26	0.851	0.04	1	0.850
Temp <= Crop	0.24	1	26	0.625	0.24	1	0.621
Temp <= ALL	2.73	4	26	0.051.	10.90	4	0.028*

Source: Data processed

Table 9 shows that the variables industrial value added, energy consumption, food crop production, and air temperature are not Granger causes at the 5% significance level. However, the results of the Granger Causality test are not an absolute measure of the cause and effect of the variables used because based on the results of the VECM parameter estimates, there are variables that significantly influence greenhouse gas emissions in Indonesia. However, the results in Table 10 indicate that the air temperature variable is a Granger cause for all variables simultaneously, this means that air temperature has a significant influence on greenhouse gases according to Granger simultaneously with other variables.

Variance Decomposition

The results of variance decomposition are used to analyze the variables that contribute most to the error variance (Benali & Feki, 2020). The contributions of lnIndustry, lnEnergy, Crop, and Temp variables are 4.67%, 1.31%, 2.30%, and 11.18%, respectively in the second period. Air temperature and industrial value-added variables have the largest contribution in explaining greenhouse gas emissions. This result is in line with the Granger Causality test which states that the industrial value-added variable has the most significant effect on greenhouse gas emissions. In addition, research by (Zhang & Ren, 2011) stated that the industrial structure experienced an increase in contribution in 2000-2005 which was related to the development of industrialization.

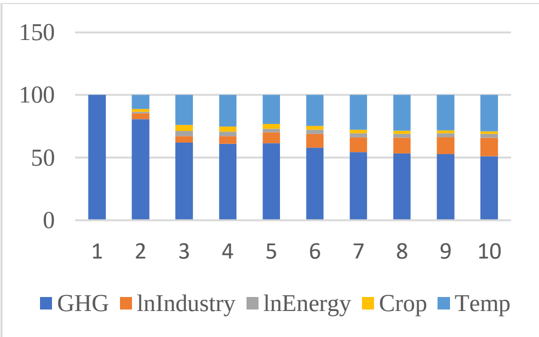

Figure 9. Decomposition of variance of greenhouse gas emissions
Source: Data processed

Figure 9 shows that in all periods, air temperature variables contribute the greatest variance to greenhouse gas emissions, and industrial value-added variables contribute the second largest variance to greenhouse gas emissions in Indonesia. This condition indicates that air temperature has a considerable role in the condition of greenhouse gas emissions in Indonesia. In addition, industrial value added is the second most contributing variable to greenhouse gas emissions because increasing industrial productivity will increase the air pollution produced because industry is closely related to the use of machinery and technology that produces emissions.

Impulse Response Function

In identifying the impact of shocks on the variables used, the impulse response function is useful to see the impact (Si et al., 2021b). Figure 9 and Figure 10 and 11 show the impulse and response of greenhouse gas emissions to the variables used. Based on Figure 10, greenhouse gas emissions give large shocks to energy consumption, crop production, and air temperature. Meanwhile, based on Figure 11, shocks from industrial value added do not have a large impact on greenhouse gas emissions because only in the second period they show a decrease. However, shocks to energy consumption, food crop production, and air temperature have a large impact on greenhouse gas emissions characterized by drastic increases and decreases in the graphs.

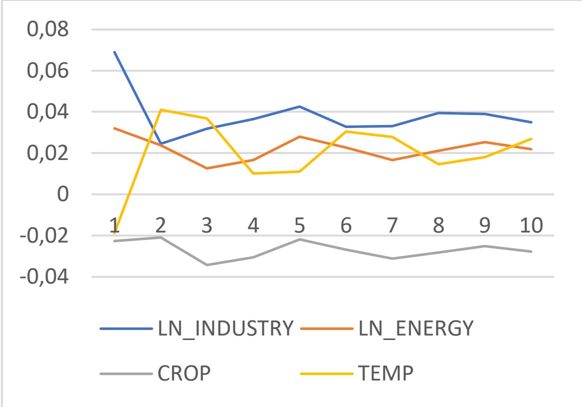

Figure 10. Greenhouse Gas Emissions Impulse to Other Variables
Source: Data processed

The impulses that greenhouse gas emissions exert against the other variables shown in Figure 10 are quite diverse. The greenhouse gas impulse to industrial value added decreased in periods 1 and 2, then increased in period 5, and until period 10 showed fairly stable conditions. The greenhouse gas impulse to energy consumption decreases in the first 3 periods and increases to period 5, then the impulse decreases to period 7 and again increases to period 9 and tends to stabilize in period 10. Greenhouse gas impulses to food crop production were in negative territory for all periods. The greenhouse gas impulse to air temperature is quite fluctuating and is in negative territory for the first period and in positive territory for other periods.

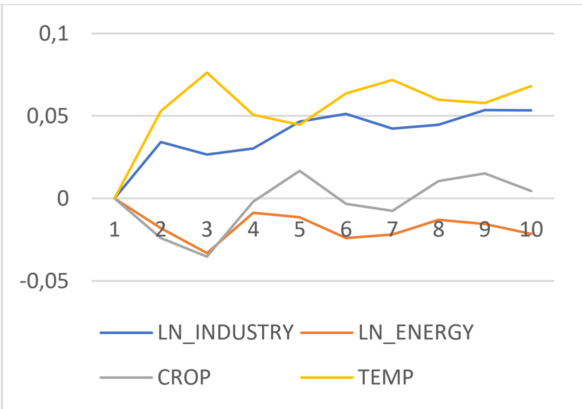

Figure 11. Response of Greenhouse Gases Emissions to Other Variables
Source: Data processed

Figure 11 shows the response of greenhouse gas emission variables to other variables. The response of greenhouse gases to the industrial value-added variable increases in periods 1 and 2 which is accompanied by a decrease in the third period, then the response continues to increase until the end of the period and the response is in positive territory, indicating that industrial value added has a positive influence on greenhouse gases in the short and long term. The greenhouse gas response to energy consumption for all periods is in negative territory, indicating that energy consumption has a negative influence on greenhouse gases in the short and long term. The response of greenhouse gases to food crop production decreases in periods 1 to 3, then increases until period 5, then decreases again in periods 6 and 7, and the response is in positive and negative territory, indicating that shocks from food crop production have an asymmetric impact on greenhouse gases in the short and long term.

Data Forecasting

R-Squared obtained in the research results (Rehman et al., 2021) as the main reference. Table 10 presents the results of forecasting the data used for 2023 to 2026. The forecasting results obtained can be used by the government or relevant stakeholders in formulating appropriate policies in order to control the rate of greenhouse gas emissions based on the variables used in this study.

Table 10. Forecasting the variables used 2023-2026

Year	GHG	Industry	Energy	Crop	Temp
2023	4.210	5.258.E+11	2694.101	3.267	26.083
2024	4.271	5.648.E+11	2800.256	3.282	26.091
2025	4.332	6.067.E+11	2910.159	3.297	26.099
2026	4.393	6.519.E+11	3024.875	3.311	26.107

Source: Data processed

Table 11. Evaluation of forecasting results

Variabel	RMSE	MAE	MAPE
GHG	0.146	0.101	2.927
lnIndustry	0.289	0.241	0.933
lnEnergy	0.064	0.053	0.723
Crop	0.120	0.105	3.521
Temp	0.108	0.081	0.310

Source: Data processed

Evaluation of the data forecasting results based on Table 11 shows good results. All variables have low MAPE values even less than 5%. This evaluation measure shows that the resulting model has good performance in forecasting the data used for the next few periods. Therefore, the results of data forecasting in this study can be a consideration for the Indonesian government in formulating policies related to environmental issues, especially greenhouse gas emissions by considering the variables used in this study.

CONCLUSION

Based on what is obtained in this study, the conclusion that can be drawn is that the Vector Error Correction Model (VECM) is used to analyze the data used because it meets the VECM requirements. This study uses 2 cointegration equations according to the Johansen Cointegration Test results. Long-term cointegration equations 1 and 2 state that there is a net effect of energy consumption, food crop production, and air temperature variables on greenhouse gas emissions. Meanwhile, the short-term equation states that there is a negative influence of the variables of industrial value added, energy consumption, and food crop production on greenhouse gas emissions. In addition, the air temperature variable has a negative influence on greenhouse gas emissions. The R-Squared value for the model obtained is 0.443. This study obtained results showing that energy consumption variables have a major influence on greenhouse gas emissions in the short term and food crop production has a major influence on greenhouse gas emissions in the long term. The use of renewable energy must be realized immediately to reduce the use of fossil energy that produces greenhouse gas emissions, especially carbon emissions. The Indonesian government as a policy maker must implement appropriate regulations for businesses in agriculture to control the use of synthetic fertilizers to reduce greenhouse gas emissions. The industrial sector that produces air pollution should filter the smoke discharged into the environment and increase the number of trees to reduce air pollution. In addition, control of fossil energy consumption must also be actively carried out by promoting the use of renewable fuels.

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