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A VECM APPROACH TO ASSESSING THE IMPACT OF ECONOMIC GROWTH, LIVESTOCK PRODUCTION INDEX, AND CROP PRODUCTION INDEX ON METHANE GAS EMISSIONS IN INDONESIA

Elgresia Egita Br Perangin-Angin[1], Hasan Bahtiar Habibi[2], Nisa Fatharani Hasna[3], [1]Fitri Kartiasih[4]
[1,2,3]DIV Statistical Computing Study Program, Politeknik Statistika STIS
[4]DIV Statistics Study Program, Politeknik Statistika STIS

ABSTRACT

Human activity has contributed to climate change in Indonesia due to its rapid economic expansion and active participation in achieving the Sustainable Development Goals (SDGs), particularly Goal 13 on climate change mitigation. This study assesses the impact of agricultural production index, animal production index, and economic growth on methane gas emissions in Indonesia using data spanning 1990 to 2020. The Environmental Kuznet Curve idea is not supported by the results of study conducted using the Vector Error Correction Model, which indicate that economic expansion and animal production have a significant long-term effect on methane (CH4) emissions. The Granger causality test reveals a considerable impact of agriculture and livestock on GDP, as well as a two-way relationship between GDP and CH4 emissions. The analysis of the Impulse Response Function reveals the various ways in which methane emissions react to independent factors like GDP, the Livestock Production Index (LPI), and the Consumer Price Index (CPI). The cattle industry has a considerable long-term impact on methane emissions, as evidenced by the fact that after a while, variations in CH4 emissions were more influenced by LPI. These results highlight the necessity for climate-friendly, sustainable policies, such as the incorporation of anticipation measures for climate change into national planning, the advancement of technology and innovation, and the control of waste from cattle and agriculture.

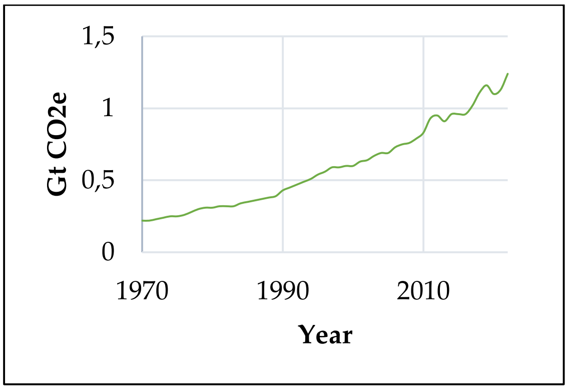
Keywords: GDP, LPI, CPI, Methane Emissions, VECM, SDGs, Time Series, EKC

INTRODUCTION

Concerns over environmental degradation are growing in the current period of economic prosperity due to rapid economic growth. Although economic growth is widely regarded as essential to the development of nations, the truth is that human activity causes this expansion to exacerbate climate change. Based on the data acquired, Indonesia had climatic changes from 2001 to 2019 for a period of 19 years (BRIN, 2023). Methane (CH_4), carbon dioxide (CO_2), nitrous oxide (NO_2), and chlorofluorocarbons (CFC) are a few of the greenhouse gases produced by human activity (Kartiasih & Setiawan, 2020; Pribadi & Kartiasih, 2020; Legionosuko et al., 2019).

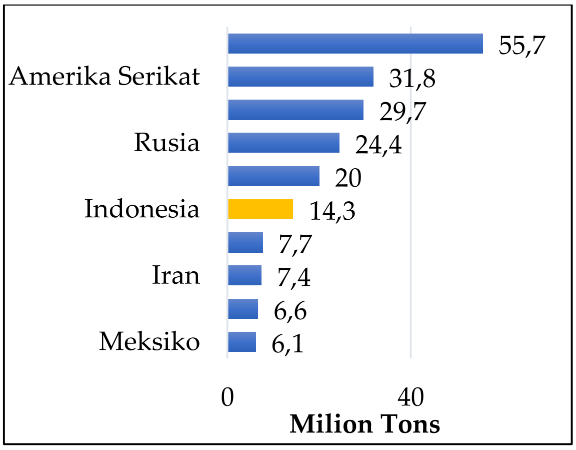
Indonesia is currently concentrating on the Sustainable Development Goals (SDGs), especially SDG 13 "Addressing Climate Change," in order to address this challenge. Including action on climate change in national plans, strategies, and policies is the goal of the 13th Sustainable Development Goal (BAPENNAS, 2015). This emphasizes how addressing the problems caused by climate change, which have far-reaching effects globally, requires a comprehensive strategy. Indonesia can handle the complexity of the environmental effects of its economic expansion by actively participating in the SDGs.

[1] Correspondence author: Fitri Kartiasih. Email: fkartiasih@stis.ac.id



Source: Katadata (2022)
Figure 1. Volume of Indonesia's Greenhouse Gas Emissions

Global greenhouse gas emissions in 2022 increased by 1.37% to 53.79 kt of CO2 equivalent, according to the European Commission's Emission Database for Global Atmospheric Research (EDGAR). Figure 1 illustrates the trend in the amount of greenhouse gas emissions from Indonesia. With 1.24 kt of CO2 equivalent emissions, which is an increase of 10% from 2021 and accounts for 2.3% of global emissions, Indonesia ranks seventh in the world (Katadata, 2022). Growing emissions of greenhouse gases (GHGs) are causing global climate change and posing a severe danger to the environment and food security. Research conducted in the Canadian province of Alberta has acknowledged the significance of agriculture in the global cycle of greenhouse emissions (Dimitrov & Wang, 2019). The agricultural sector is a major player in this dynamic, contributing significantly to GHG emissions. The cattle sector is a major source of greenhouse gas emissions, according to research (He et al., 2023) that sampled Chinese reality. Further research indicates that the rise in global emissions is largely attributed to per capita consumption and technological progress (Sun et al., 2022).



Source: Katadata (2022)
Figure 2. Ten Countries with the Largest Global Anthropogenic Methane Emissions (2022)

Even though methane has a shorter atmospheric lifetime, it has been responsible for almost 30% of the rise in global temperatures during the Industrial Revolution.

By 2022, methane production will reach 580 million metric tons worldwide (International Energy Agency, 2022). With 141,954 kt, the IEA found that the agriculture sector was the largest donor. Waste (70,759 kt), energy (133,351 kt), and other sectors (9,738 kt) were the next highest contributors. The agricultural sector in Nigeria significantly contributes to greenhouse gas emissions and the country's impact on global warming (Okorie & Lin, 2022). Methane gas emissions are mostly caused by the agriculture sector, particularly by cattle (Dangal et al., 2017). Methane emissions (CH_4) are adversely affected by agricultural productivity (Rashid & Gopinathan, 2023). Roughly 29% of all methane emissions worldwide are attributed to the agricultural sector, which includes industry (Kuhla & Viereck, 2022). One of the main causes of CH4 emissions both globally and regionally is the cattle industry, which also contributes to enteric fermentation and manure management (Yu et al., 2018). Given that the primary industry and source of revenue in developing nations like Indonesia is agriculture, it is intriguing to investigate in this study why Indonesia ranks sixth globally in methane gas production, with 14.3 million metric tons produced (Figure 2).

Prior research has demonstrated that methane gas emissions, one of the main greenhouse gases, have a big influence on environmental sustainability and climate change (Wu et al., 2023). A related study conducted in Sudan revealed that the growth of the economy, the expansion of agriculture, and energy consumption all significantly affect CH_4 emissions (Mohamed, 2020). Meanwhile, in Argentina (Puliafito et al., 2020), Austria (Hörtenhuber et al., 2022), and Egypt (Aboul Ela, 2023), variables including energy consumption, GDP, livestock production, and use of agricultural fertilizer also play significant roles in CO_2 and CH_4 emissions.

It was discovered that the Vector Error Correction Model, or VECM, outperformed the ARIMAX model in timeseries data forecasting (Aboul Ela, 2023). We may estimate the long-term effects of time series data as well as the short-term effects between variables using VECM. Previous research has shown a strong positive association between environmental pollution and cattle husbandry. Furthermore, according to (Ratna et al., 2023), the Granger Causality Test suggests that the growth in methane emissions is influenced by both GDP per capita and livestock output. In this case, a critical indicator of economic growth is the country's gross domestic product (GDP). Although the expansion of livestock production contributes to the short-term rise in methane emissions, it is an intriguing finding that there is no significant relationship between methane emissions and GDP over the long term, according to the Environmental Kuznet Curve (EKC) concept (Ratna et al., 2023). This result lends credence to the theory that environmental degradation is first exacerbated by economic growth, reaches a threshold, and then starts to decrease.

Methane emissions are a major worldwide concern since methane (CH_4) has a warming potential that is 25 times more than that of carbon dioxide (CO_2) as a greenhouse gas (Djoumessi Djoukouo, 2021). Referring to earlier research that indicates that agriculture can be a significant contributor to methane emissions (Rashid & Gopinathan, 2023) and the livestock sector as a large contributor to methane emissions (Xu et al., 2019), this study not only looks at the effect of economic growth on methane emissions but also pays particular attention to the role of the agricultural sector. The reduction of livestock numbers by government laws in response to environmental concerns, particularly methane, creates a complex dynamic between greenhouse gas emissions and economic growth (Bai et al., 2021).

These days, the focus on lowering CO2 emissions is being replaced by lowering emissions of methane, a strong greenhouse gas that contributes to the creation of ozone at Earth's surface. Because methane breaks down more quickly than CO2, its immediate impacts are of greater concern. Low-carbon regulations have been enacted in many industrialized and developing nations, but methane emissions have not received enough attention. Since that agriculture is the primary industry and source of wealth in developing nations like Indonesia (Kartiasih et al., 2022; Kartiasih & Setiawan, 2019; Harum et al., 2023; Wardana et al., 2023), methane emission reduction strategies such using technology and innovation in the agricultural sector can significantly aid in achieving the SDGs. Innovation and technology (IT) have been key factors in recent decades in promoting environmental sustainability and agricultural productivity (Qayyum et al., 2023).

The primary goal of this research is to contribute to a better knowledge of Indonesia's environmental dynamics, particularly as they relate to economic growth, the environment, and the mitigation of methane emissions. Thus far, no comparable study employing the Vector Error Correction Model (VECM) has been carried out in Indonesia. We chose the variables of economic growth, livestock production index, and crop production index from peer-reviewed publications and other studies to investigate their impact on methane emissions in Indonesia. In addition to obtaining the best model to see the factors that affect methane emissions in Indonesia and demonstrate whether it satisfies the concept of the Environmental Kuznet Curver (EKC), this model is anticipated to provide a clearer picture of whether there is short- and long-term effects of economic growth, livestock production, and crop production on methane emissions. Indonesia was selected as the case study subject because of its distinct features related to economic, agricultural, and environmental resilience.

This research can serve as a foundation for developing national policies aimed at mitigating climate change, given a better understanding of the variables influencing methane emissions from this industry. This is significant because the dynamics of methane emissions are significantly influenced by the agricultural sector, and better understanding the intricate relationships between economic growth, crop output, and livestock production can lead to more efficient policy planning. All things considered, this study offers fresh and insightful perspectives on the intricate connection between Indonesia's economic development, agricultural practices, and methane emissions. The existing research is enhanced by the growing detail of the effects of crop output, livestock production, and economic expansion on methane emissions. In addition to offering scientific insights, the results should assist the government in developing more focused, sustainable, and climate-friendly agricultural policy.

This study has the potential to significantly reduce Indonesia's greenhouse gas emissions, especially given the growing global awareness of climate change. Taking into consideration the effects on the environment, this study can guide the nation toward sustainable development, which aligns with the Sustainable Development Goals (SDGs), especially SDG 13 "Addressing Climate Change." It is anticipated that the study's findings will offer a strong foundation for practical measures and regulations that aid in the worldwide endeavor to address climate change.

DATA AND METHODOLOGY

Secondary data from four variables—the Gross Domestic Product (GDP), the Livestock Production Index, the Crop Production Index, and CH_4 Emissions—are used in this analysis. The data utilized spans the years 1990–2020 and contains annual statistics for Indonesia. The World Bank provided the information for the four variables. To lessen heteroscedasticity, the GDP variable and the CH_4 emission variable underwent a natural logarithmic transformation.

Table 1. Variables used in the study.

Variables	Unit	Source
Methane Emissions (CH_4)	kt CO_2 equivalent	Methane Emission Data
Gross Domestic Product (PDB)	Current US$	Gross Domestic Product Data
Livestock Production Index (LPI)	Index (2014-2016 = 100)	Livestock Production Index Data
Crop Production Index (CPI)	Index (2014-2016 = 100)	Crop Production Index Data

Source: World Bank (2023)

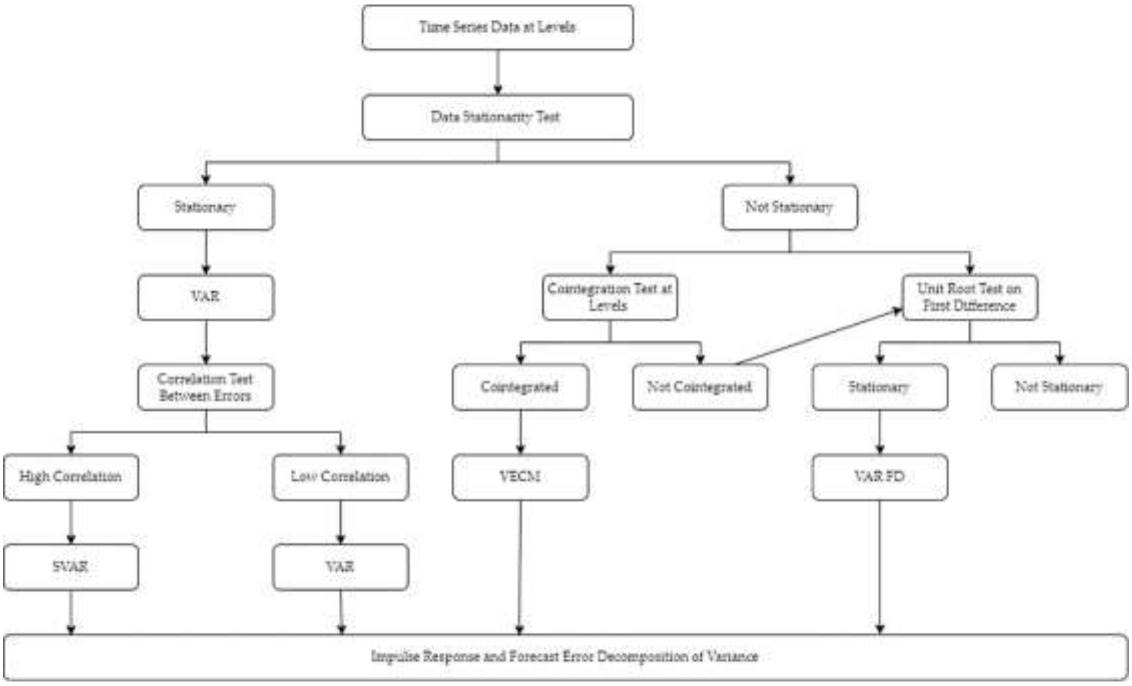


Figure 3. Flowchart of research stages

Unit Root Test

An initial test (assumption) to determine if a variable is stationar is called a unit root test. One requirement for using VECM is that variables be stationar. Every time series variable used in the building of this system has to meet the requirement of stationarity (Granger & Newbold, 1974). According to (Wei, 2006), the stationarity under consideration is both stationary to the mean and to the variance. This is due to the fact that the stationarity of the time series data will have a significant impact on the cause and effect of variables when examining causality (Stock & Watson, 1989). In this study, the Dickey-Fuller (DF) test was developed into the Augmented Dickey-Fuller (ADF) test, which we utilize to determine the stationarity of the data.

$$\Delta Y_t = \beta_1 + \beta_2 t + \delta Y_{t-1} + \Sigma \alpha_i \Delta Y_{t-1} + \varepsilon_t$$

where the first difference is represented by Δ and the time series variable t is indicated by Y_t. This is the hypothesis that was applied in the ADF test (Gujarati & Porter, 2008).

$H_0 : \gamma = 0$ (there are unit roots, data is not stationary)

$H_1 : \gamma \neq 0$ (no unit roots, stationary data)

When the probability value is less than

the probability value, the data series is considered to be stationary. For this study, we employ α = 5%. The next transformation, known as differencing, is carried out if the data collected is not steady at the level. The process of differencing involves generating a new value from the difference between the observation and the observation from the prior period. The data of GDP, LPI, CPI, and CH_4 emissions are expected to be stationary at the first differencing in this study.

Optimum Lag and Stability Test

The next stage is to ascertain data stability and the ideal lag based on VAR techniques after acquiring proof that the data satisfies stationarity at the first differencing. The goal of data stability is to determine how far behind time the data is steady. In order to determine the ideal lag, data stability must be met (Hawari & Kartiasih, 2017; Kartiasih et al., 2012). The optimal lag will be determined using the results as interval limits. If the modulus in the AR Roots table that is generated is not greater than one, data stability will be satisfied.

Moreover, there are five widely used criteria that can be used to determine the ideal lag: the LR statistic test, the Schwarz information criteria (SC), the Hannan-Quinn information criteria (HQ), the Akaike information criteria (AIC), and the Final Prediction Error Criterion (FPE). The appropriate latency is typically not chosen by these factors. Consequently, choosing the lag with the highest number of satisfied criteria is the best option. Assuming that the causality test, residuals, etc., yield superior results, the optimal lag may occasionally be determined by examining only the AIC criterion. To calculate the lag interval for the cointegration test, this ideal lag will be leveraged (Ningsih & Kartiasih, 2019; Pertiwi et al., 2023).

Johansen Cointegration Test

A linear combination of correlations between variables that are not stationary at levels is known as cointegration. Since every variable needs to be integrated at the same level, the finding that every variable is cointegrated suggests that every variable is following the same stochastic trend. Put another way, over time, these variables will move in a comparable direction (Nugraha & Osman, 2019). If there is a long-term relationship between time series variables, it can be found using the cointegration test (Gujarati & Porter, 2008). Static data are needed for cointegration testing. The variable cannot be cointegrated if at least one of the variables has a distinct level of integration (Engle & Granger, 1987).

The Johansen Cointegration Test, which employs the Max-Eigen and trace tests, is the test used to verify data cointegration. When the trace test value exceeds the critical value, data cointegration can be satisfied. The variables are known to have a long-term association when data cointegration is satisfied. The model of the Johansen's cointegration test is as follows (Johansen, 1988).

$$Z_t = \alpha + \tau_1 Z_{t-1} + \cdots \tau_p Z_{p-1} + \varepsilon_t$$

where Z_t is a $(n \times 1)$ dimensionless vector that adheres to $I(1)$. Next, a brief description of the test's nature.

Trace Test

The likelihood ratio test for the trace matrix is used in this test, and it is subsequently changed to adhere to the subsequent test statistics (Johansen, 1988)

$$\hat{J}_{trace} = -T \sum_{i=r+1}^{n} \ln(1 - \hat{J}_i)$$

Where T indicates the sample size used and $\hat{J}_i$ is the eigenvalue estimate ordered from largest to smallest.

Max-Eigenvalue Test

The likelihood ratio test for the eigenvalue matrix is also used in this test, and it is then changed to adhere to the test statistics listed below (Johansen, 1988)

$$\hat{J}_{trace} = -Tln(1 - \hat{J}_{r+1})$$

In this case, the meaning of T and J is the same as the trace test. The following hypothesis applies to both tests:

H_0: There are at most r cointegrating equation (CE)
H_1: There are as many as n CE

If r is at least 1, cointegration can be satisfied, so n=2. The Vector Error Correction Model (VECM) can be used if the presumptions of data cointegration and data stationarity at differencing 1 are satisfied. Nevertheless, Vector Autoregression (VAR) will be used if cointegration is not reached at this point.

VECM model

This study analyzes the long- and short-term correlations between GDP, LPI, CPI, and methane emissions using the VECM model. The VECM can be used if the presumptions of cointegration and stationarity at first differencing are satisfied. In this work, we aim to investigate the relationship between methane emissions (CH_4) and economic growth as measured by GDP, livestock production index (LPI), and crop production index (CPI). Therefore, the VECM equation model used for this study is

$$\Delta lnCH_4 = \alpha_0 + \sum_{i=1}^{p} \beta_{1i}\,\Delta lnCH_{4(t-i)} + \sum_{i=1}^{p} \beta_{2i}\,\Delta LPI_{t-i} + \sum_{i=1}^{p} \beta_{3i}\,\Delta CPI_{t-i} + \sum_{i=1}^{p} \beta_{4i}\,\Delta lnPDB_{t-i} + \psi ECT_{t-1} + \varepsilon_t$$

where β and ψ represent the coefficients on the variable and p represents the number of lags utilized in the VECM model. While ECT displays the independent factors that impact how well feedback works throughout the error-correction phase. It is also possible to ascertain from the model if one independent variable affects the other in the short- and long-terms.

Granger Causality Test

By examining the likelihood value based on the probability of significance, the model that has been developed can be utilized to examine the incidental impact between one variable and another. The average VECM model can then be determined using the short-term Granger causality estimates (Engle & Granger, 1987). The formula used in the granger causality method is as follows:

$$X_t = \sum_{i=1}^{m} a_i X_{t-i} + \sum_{j=1}^{n} b_j Y_{t-j} + u_t$$

$$Y_t = \sum_{i=1}^{r} c_i Y_{t-i} + \sum_{j=1}^{s} d_j X_{t-j} + v_t$$

Where, $a, b, c,$ and d are coefficients that indicate a two-way relationship between variables. While u_t and v_t are *error terms* that are assumed to have no serial correlation in them with the condition of $m = n = r = s$.

Based on the formula, there are the following conditions:

a. If both coefficients are 0, then there is no causality between variables
b. If one of the coefficients is 0 and the other is not, then there is one-way causality of the variable whose coefficient is not 0.
c. If both coefficients are not equal to 0, then there is bidirectional causality between the two variables.

Impulse Response Function (IRF)

The VECM model, which is created by shock-fitting each variable to the endogenous variable—in this case, CH_4 emissions is dynamically exhibited using the impulse response function. Every variable's response to change is quantified in standard deviation units and begins when the shock for that variable occurs. The identification method employed is the error covariance matrix's Cholesky decomposition (Enders, 2004).

Variance Decomposition

Variance decomposition is similar to IRF in that it views the system's dynamics. In order to examine the effects of random disturbances on the developed VECM model, decomposition is carried out on endogenous variables. Each model variable that potentially have an impact on endogenous variables will have its variance of forecast errors broken down via variance decomposition.

RESULT AND DISCUSSION

Indonesia's Gross Domestic Product,

Livestock Production Index, Crop Production Index, and Methane Emissions Overview from 1990 to 2020

To choose the best econometric technique, it is essential to comprehend the properties of the variables used in the study object. A profound comprehension of the fundamental characteristics of the observed variables is necessary for econometrics, a subfield of economics that integrates theory and statistical techniques to test hypotheses and provide predictions. The number of observations, mean, minimum value, maximum value, standard deviation, and variance are examples of descriptive statistics that are required to obtain a comprehensive image of the data distribution.

Table 2. Descriptive Analysis

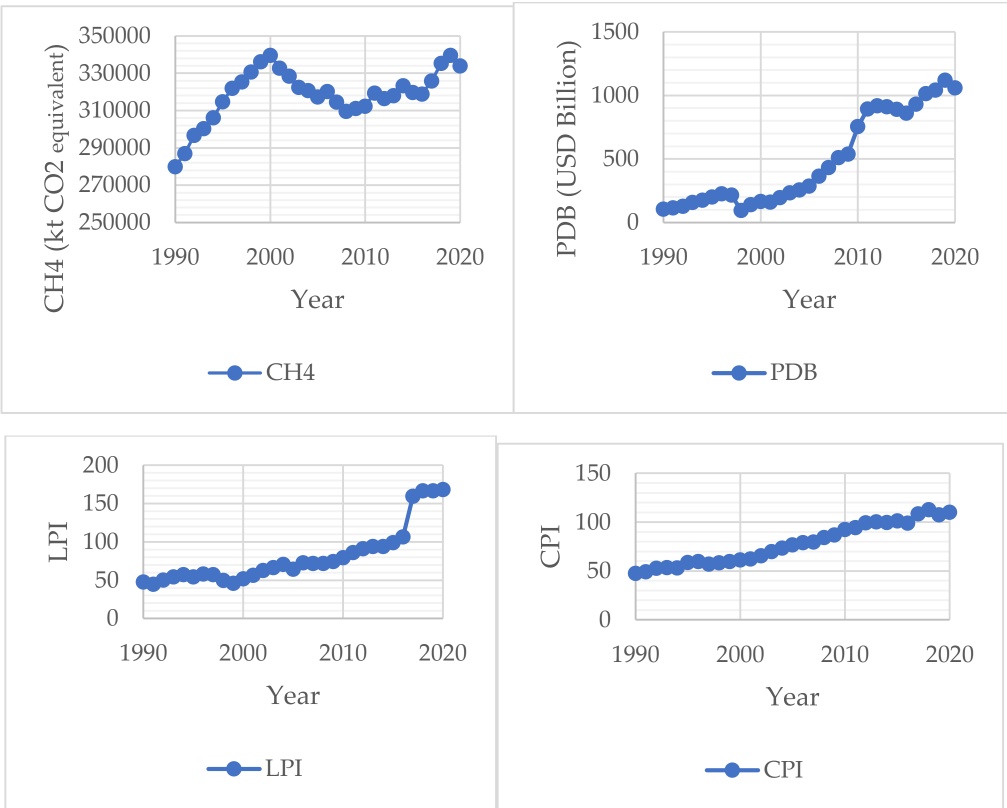
Variables	N	Mean	Min	Max	Std. Dev.	Varians
CH_4	31	318722,656	280038,514	339713,820	14110,439	199104501,346
PDB	31	4,874E+11	95445547873	1,119E+12	3,653E+11	1,33453E+23
LPI	31	80,542	44,990	168,310	37,078	1374,801
CPI	31	77,928	47,77	112,73	21,044	442,861

Source: World Bank (2023), data processed

From the results of data exploration contained in Table 2, several preliminary conclusions were obtained regarding the characteristics of the *dataset* used in this analysis. From Table 2, it can be concluded that the data used in the analysis is 31 *rows of* data, in this case using annual data. The average CH_4 emission is 318722.656 kt CO_2 equivalent$_2$; the average GDP is 4.87408E+11 US$; the average LPI is 80.542; and the average CPI is 77.928. In addition, the standard deviation of each variable can be used to see an overview of the data distribution. The standard deviation of CH_4 emissions is 14110.439 kt CO_2 equivalent$_2$; the standard deviation of GDP is 3.65312E+11 US$; the standard deviation of LPI is 37.078; and the standard deviation of CPI is 21.044. It should be observed that there is a great amount of scatter in the GDP and CH_4 emissions data, which could indicate significant fluctuation within the dataset. Thus, the GDP and CH_4 emissions variables were first converted using the natural logarithm in order to address heteroscedasticity. The goal of this modification is to lessen the data's high variability so that additional interpretation and analysis will be made easier.

Initial Data Exploration

Before conducting additional studies, a thorough grasp of the features and patterns of the data is provided by the initial study of the data using data plots. Researchers and analysts may quickly understand the distributions, correlations, and anomalies in the dataset at hand thanks to data plots, which offer a visual depiction of the data.



Source: World Bank (2023)

Figure 4. Data Plot of Methane Emissions, Gross Domestic Product, Livestock Production Index, and Crop Production Index in Indonesia in 1990 – 2020

A visual analysis, as illustrated in Figure 4, can be carried out to provide a greater understanding of the trends and changes in the four observable variables. Figure 4 illustrates how the four variables have an increasing tendency during the course of the years under observation. 2000 had the highest levels of CH_4 emissions. 2019 saw the highest GDP. 2020 saw the LPI reach its maximum. 2018 saw the CPI reach its maximum. The four variables' stationarity qualities warrant particular attention despite the obvious increasing trend. The four variables are suspected of being non-stationary due to the notable fluctuations and differences in their time patterns. Stationarity is crucial in time series analysis because it influences both the model's output and how the findings are interpreted.

Unit Root Test

It is essential to be aware of the stationarity of the data, both in level and initial differencing, prior to initiating a battery of tests to ascertain the VECM model. To determine if a timeseries is stationary or not, the next step is to do a unit root test first. Table 3 displays the unit root of each variable that was used, including first differences and levels. Every variable at the level has a unit root, according to the findings of the ADF test at a significance level of 5%, showing behavior that is trending upward with time. Differencing is required if the variables at the level exhibit non-stationarity or have unit roots. All of the variables do not have unit roots at the first differencing, indicating that stationarity has been met. Thus, the VECM modeling's initial premise has been validated, and the process may go on to the next step, which is to identify the data's equilibrium and ideal lag.

Table 3. Unit Root Test

Variables	Augmented Dickey-Fuller	
	t-Statistic	**Prob.***
$LnCH_4$	-2.866707	0.0617
$D.lnCH_4$	-3.107286**	0.0371
LnPDB	-0.797988	0.8053
D.lnPDB	-5.472687**	0.0001
CPI	-0.155243	0.9340
D.CPI	-5.941149**	0.0000
LPI	1.052421	0.9961
D.LPI	-4.543494**	0.0012

* Probability using MacKinnon (1996) one-sided p-value
** Indicates that there are no unit roots. In other words, the variables are stationary at that level This can also be seen through the Prob. value which has a value less than 0.05.
Source: World Bank (2023), data processed

Optimum Lag and Stability Test

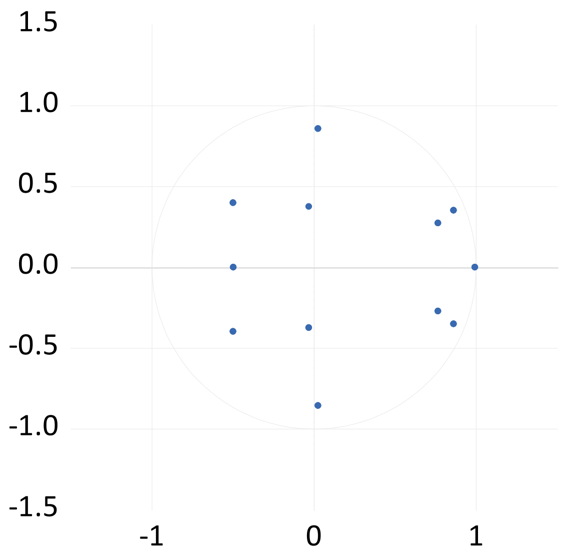
Furthermore, Figure 5 and Table 4 can be used to assess the data's stability and the best lag that was chosen. It is evident from Figure 5 that there aren't any points outside of the circle. It may be concluded that the data used exhibits good stability across the observed time range since there are no spots outside of the circle. When it comes to time series analysis, data stability is essential since it guarantees that variations or oscillations are consistent and not excessive. It can be presumed that the data is steady at that lag interval as the lag interval that is being used is lag 1 to lag 3. Furthermore, as Table 4 illustrates, the lag interval can be used as a limit to determine the ideal lag. Table 4 shows the ideal lag as determined by multiple criteria: LR, FPE, AIC, SC, and HQ. The ideal lag length is indicated by each value in the LR, FPE, SC, and HQ criteria to be lag 1, whereas the optimal lag length is indicated by the AIC criterion to be lag 3. Generally speaking, the lag that best meets the most requirements is chosen as the ideal latency; in this instance, that lag is 1.

Nevertheless, it is evident that lag 1 is not cointegrated in the model following the pre-testing of lags 1 and 3. Cointegration is a crucial idea that shows how the variables are related over the long term. Therefore, lag 1 cannot be the best latency to utilize for figuring out the VECM model. However, with the assumption of a deterministic trend, lag 3 displays cointegration versus a variety of models, allowing the hunt for VECM models to continue. Lag 3 was chosen as the ideal lag in this investigation taking these factors into account. In order to ensure that the model is accurate and sustainable in its representation of the relationships that actually exist in the time series data, the ideal lag must be chosen by striking a balance between model criteria and significant analytical results.

Table 4. Optimal Lag Selection

Lag	LR	FPE	AIC	SC	HQ
0	NA	3.107605	12.48524	12.67555	12.54342
1	169.4804*	0.006241*	6.259384	7.210958*	6.550289*
2	19.44425	0.007611	6.378859	8.091694	6.90249
3	20.60689	0.007478	6.147924*	8.622018	6.904729

Notes: * indicates the lag selected based on the criteria. However, in this study, lag 3 will be selected that meets the AIC criteria with consideration of data cointegration and the VECM model.
Source: World Bank (2023), data processed



Source: World Bank (2023), data processed
Figure 5. Graph of AR roots with lag interval 1-3

Johansen Cointegration Test

To ascertain the long-term relationship between the variables, a Johansen cointegration test will be performed in the following stage. It is crucial to confirm that the deterministic trend assumption relating to the data's cointegrity has been met before starting such a test. This is confirmed by looking at Table 5. Every model satisfies the cointegration assumption, as Table 5 demonstrates. Based on the data distribution on GDP, LPI, CPI, and CH_4 emissions, a linear intercept and trend model (M4) will be employed. The distribution of the data and the features of the observed variables have been taken into account in making this selection.

The Johansen cointegration test is performed using Trace and Max Eigen statistics to ascertain whether a cointegration relationship exists in a time series system. The Johansen cointegration test outcomes utilizing Trace and Max-Eigen statistics are displayed in Table 6. The trace and max-eigen statistics values will be provided for every cointegration equation (CE). When a CE's trace or max-eigen statistical data exceed its Critical Value, it is considered to have fulfilled cointegration. The table indicates that there are three CEs that satisfy cointegration, and this leads to the observation of the three equations' long- and short-term causal relationships. The following stage involves analyzing the VECM model-based long- and short-term relationships between the variables.

Table 5. Model selection based on deterministic trend assumption

Test Type	M1	M2	M3	M4	M5
Trace	3	4	2	3	3
Max-Eig	1	4	3	3	3

Notes: M1: Model without intercept and trend; M2: Model with intercept and no trend; M3: Model with intercept and no linear trend; M4: Model with intercept and linear trend; M5: Model with intercept and quadratic trend, Determination based on MacKinnon-Haug-Michelis (1999).
Source: World Bank (2023), data processed

Table 6. Johansen Cointegration Test

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistics		Max-Eigen Statistics	
		Value	alpha = 0.05	Value	alpha = 0.05
r = 0*	0.789389	105.5109	63.8761	42.05903	32.11832
r <= 1*	0.673043	63.45191	42.91525	30.18398	25.82321
r <= 2*	0.578208	33.26793	25.87211	23.30755	19.38704
r<=3	0.308508	9.960381	12.51798	9.960381	12.51798

Notes: *indicates the null hypothesis is rejected at the 0.05 level, in other words, it fulfils the cointegration assumption.
Source: World Bank (2023), data processed

Developing the VECM Estimation Model

The results of the conducted Johansen cointegration test show that the variables in the time series system have a long-term relationship. Developing an appropriate estimating model is the next stage. The Vector Error Correction Model (VECM) is a frequently employed method. Table 7 displays the outcomes of comparing the independent variable ($lnCH_4$) to the long-term association between the variables lnPDB, CPI, and LPI. If the absolute value of the t-statistic exceeds the critical value of 5%, which is 2.0452, then a variable is considered to have a significant long-term connection. In this situation, the observation value from the previous period can be inserted into the equation model of the dependent variable for current period if a variable has a substantial long-term influence. Table 7 indicates a strong long-term impact of trend, LPI, and lnPDB on $lnCH_4$. This suggests that over a longer time span, variations in the lnPDB and LPI variables, along with the time trend, consistently affect the amount of methane emissions ($lnCH_4$). This suggests that these variables have a significant influence on how methane emissions evolve over time. On the other hand, the CPI lacks sufficient data to demonstrate a meaningful long-term correlation with $lnCH_4$. Although not insignificant, this could suggest that over longer timescales, the CPI variable has too little or no effect on methane emission levels.

The findings we obtained are consistent with studies carried out in Sudan and Egypt concerning the extended relationships between economic expansion, agricultural expansion, and greenhouse gas emissions (Aboul Ela, 2023; Mohamed, 2020), wherein the long-term association of agricultural growth is disregarded. A number of studies in this context do not meet the criteria of the Environmental Kuznet Curver (EKC), such as our own, which indicates that environmentally friendly economic development policies are required and should be applied. These policies include considering or giving higher priority to environmental policies once certain income levels are reached, such as investing in environmentally friendly technology and emphasizing the value of education and environmental conservation awareness. Another study conducted in Indonesia (Iskandar, 2019) also reveals a long-term relationship between economic growth and CO_2 emissions.

For additional analysis and decision-making, these results serve as a reference. Four Building upon the success of GDP, LPI, and trend factors, more focused policy measures for managing CH_4 emissions can be developed. The impact of these variables is detailed in this work, which makes a significant contribution to our understanding of the factors that influence methane emission levels over time. Researchers and policymakers can establish pertinent and useful policies using this interpretation.

Table 7. Long-term influence on CH emissions of4 based on the formed model

Value	lnCH4 (-1)	LnPDB(-1)	CPI(-1)	LPI(-1)	@TREND(1)	C
Coefficient	1	0.549462	-0.015705	0.012068	-0.04614	-26.27816
SE		0.12991	0.0183	0.00318	0.01726	
t-Statistics		4.22971*	-1.4505	3.7949*	-2.67336*	

Notes: *shows statistical value > 5% critical value

Source: World Bank (2023), data processed

We can evaluate the variables' effects on the long-term relationship before moving on to the short-term relationship. Table 8 shows the link between independent variables and CH_4 emissions over a short time. A number of variables are significantly implicated in the short-term relationship with the dependent variable, according to the results of the same examination of the long-term relationship. The long-term model is applicable, as demonstrated by CointEq1's strong t-statistics. Next, a strong short-term association between $lnCH_4$ and the variables $\Delta(lnPDB(-2)$, $\Delta(CPI(-1)$, $\Delta(LPI(-1)$, $\Delta(LPI(-3)$ is observed. Depending on the dependent variable, the value enclosed in parenthesis can be understood as the prior observation period's position. Therefore, even though the independent variables employ a specific period, they all have a short-term connection with $lnCH_4$.

Table 8. VECM model for short-term relationship

Error Correction	Coefficient	SE	t-Statistics
CointEq1	0.121061	-0.04245	[2.85187]*
D(lnCH4(-1))	-0.232788	-0.32177	[-0.72345]
D(lnCH4(-2))	-0.49257	-0.25945	[-1.89853]
D(lnCH4(-3))	0.264155	-0.24938	[1.05924]
D(lnPDB(-1))	-0.045574	-0.02312	[-1.97123]
D(lnPDB(-2))	-0.051157	-0.02192	[-2.33423]*
D(lnPDB(-3))	-0.003826	-0.01792	[-0.21354]
D(CPI(-1))	0.004158	-0.00176	[2.36254]*
D(CPI(-2))	0.000814	-0.00186	[0.43817]
D(CPI(-3))	0.001256	-0.00175	[0.71661]
D(LPI(-1))	-0.001256	-0.00057	[-2.21733]*
D(LPI(-2))	-0.000858	-0.00053	[-1.62254]
D(LPI(-3))	-0.001604	-0.00054	[-2.97223]*
C	0.017339	-0.00966	[1.79428]

* Indicates a significant variable has a short-term relationship with the dependent variable

Source: World Bank (2023), data processed

By involving table 7 and table 8, a VECM model can be built based on the variables of this study, which is as follows:

$$\begin{aligned}\Delta(lnCH_4) = 0.1211\big(lnCH_4(-1)\big) &+ 0.0665\big(lnPDB(-1)\big)\\ &+ 0.0015\big(LPI(-1)\big)\\ &- 0.0056(@TREND)\\ &- 0.0512\big(\Delta lnPDB(-2)\big)\\ &+ 0.0042\big(\Delta CPI(-1)\big)\\ &- 0.0013\big(\Delta LPI(-1)\big)\\ &- 0.0016(\Delta LPI(-3)\\ &- 3.1823\end{aligned}$$

The model indicates that $lnCH_4$ from the prior era has the largest coefficient, having a positive impact of 12.11% on the value of $lnCH_4$. Next in line is lnPDB from the same time, which has a positive impact of 6.65%. The prior period's highest coefficient on $lnCH_4$ indicates that the state or volume of CH_4 emissions during that time had a major influence on the variable itself. To be more precise, there was a 1% increase in CH_4 emissions in the preceding period and a 12.11% increase in the subsequent period. Moreover, the preceding period's lnPDB of 6.65% shows a positive influence, indicating that rising GDP and economic growth both significantly contribute to rising CH_4 emissions in the ensuing era. This is in line with the EKC principle's description of the relationship between rising economic activity and methane emissions. Conversely, the LPI variable from the prior period increased the value of CH_4 emissions by only 0.15% for every unit increase in the index. In other words, the variables GDP, LPI, and ΔCPI significantly positively affect the value of CH_4 emissions in the upcoming period. In the short run, however, a rise in other variables will lessen the decrease in CH_4 emissions.

Furthermore, it's critical to understand how to assess the model. A critical first step in determining the model's ability to accurately anticipate future events and explain the variability of methane (CH_4) emission levels is evaluating the created statistical model. Table 9 gives the model's representation of the CH_4 emissions. As can be shown, the R-squared value is equal to 0.6948, indicating that 69.48% of the variation in methane emissions can be described by the model in use, with the remaining 30.52% being explained by other factors. This indicates that while the model's unexplained variation is rather high, the model generally performs well.

Table 9. Model Evaluation

Parameters	Value
R-squared	0.694846
Adj. R-squared	0.389693
Sum sq. resids	0.001978
S.E. equation	0.012335
F-statistic	2.277039
Log likelihood	90.2297
Akaike AIC	-5.646645
Schwarz SC	-4.974729
Mean dependent	0.00392
S.D. dependent	0.015789

Source: World Bank (2023), data processed

Nevertheless, the number of significant variables in the model is not taken into account in the R-squared computation. It would be preferable to assess the model using the adj. R-squared parameter because the model created has a number of variables that are not significant. With an Adj. R-Squared value of 0.3897, the model built using the variables at hand is able to account for 38.97% of the variation in CH_4 emissions. Since other variables with more significance—namely, 61.03%—explain a larger portion of the variation, this statistic tends to be tiny. According to Table 7, which is a part of the model, this indicates that the agriculture index is an inconsequential variable in the model. However, several variables are not included in the model even though they are significant for CH_4 emissions. Countless businesses, cattle areas, landfills, and so on are examples of potential variables. According to (Peng et al., 2016), the coal sector is the primary human source of CH_4 emissions, even in China. Other factors that have a substantial impact on CH_4 emissions must therefore be included will enhance the VECM method-derived model.

Granger Causality Test

The Granger causality test is also used to evaluate how well some variables can predict changes in other variables over a given period of time. The Granger Causality results based on VECM model results are shown in Table 10. The table indicates that, at the 5% significance level, GDP has a significant impact on CH_4 emissions, and at the 10% significance level, CH_4 emissions has an impact on GDP. This demonstrates the two-way relationship between GDP and CH_4 emissions, with the effect on GDP being less than the other way around. fourThis shows that changes in the environment, in this case CH emissions, will have an indirect impact on Indonesia's GDP growth rate. Given that environmental changes, like air pollution, can lower human productivity and have an effect on the expansion of the economic sector, this is highly probable to occur. Therefore, to ensure the stability of national economic growth, environmental changes brought on by CH_4 emissions must be predicted and appropriately controlled to the greatest extent possible.

Table 10. Granger Causality Test Results in the VECM Model

DV	Short-run()			
	$\ln CH_4$	**lnGDP**	**CPI**	**LPI**
$\ln CH_4$		7.135107*	5.554279	1.102566
lnGDP	8.966758**		3.041893	0.415409
DCPI	6.82329*	8.563399**		2.436146
DLPI	9.144347**	13.73002***	0.912102	

*, **, ***, indicate significance at the 10%, 5%, 1% level, respectively.

Source: World Bank (2023), data processed

Table 10 also demonstrates the impact of LPI and CPI on CH_4 emissions, with the latter two variables being significant at the 5% and 10% levels, respectively. The amount of CH_4 emissions created will grow in response to increases in CPI and LPI, with LPI having a greater overall impact than CPI. Prior studies using the Granger causality test showed that the rise in CH_4 emissions was caused by both GDP per capita and animal production (Ratna et al., 2023). In accordance with the demand for food, several studies have also demonstrated that the agricultural sector influences global methane emissions by 40–60% (Miskat et al., 2020; Saini & Bhatt, 2020; Searchinger et al., 2021). For LPI and CPI, on the other hand, this relationship is not bi-directional because CH_4 emissions do not significantly affect either variable, even at the 10% significance level. Thus, it is impossible to control environmental change in a way that would alter LPI and CPI.

Table 10 revealed that, at the 1% and 5% significance levels, the LPI and CPI significantly affect the national GDP number in addition to their association with CH_4 emissions. This suggests that of all the research variables considered, the LPI has the most impact on economic growth in Indonesia, followed by the CPI's influence. This is due to the fact that a rise in the production index of agriculture (such as crops and grass) and livestock (such as meat, milk, manure, etc.) will undoubtedly result in an increase in the GDP figure. Thus, improving the livestock and agricultural industries could lead to higher economic growth in Indonesia in the future. In this instance, the government can improve people's economic welfare by taking into account the livestock and agriculture sectors as policy holders.

Additionally, the study variables that were used do not significantly affect the CPI and LPI variables, according to our data. No discernible relationship was found between the rise or fall in LPI and GDP, CPI, or CH_4 emissions. The CPI demonstrates that there is no discernible relationship between GDP, LPI, or CH_4 emissions. Given that there is no direct participation in either of the two variables—GDP or CH_4 emissions—these results suggest that it is not possible to predict the LPI or CPI using these variables alone. This further shows that the LPI and CPI are unrelated to one another, meaning that modifications to one will not have an impact on the other. Thus, in order to enhance both sectors, policymakers should think about creating distinct policies.

Impulse Response Function

The impulse response function is an economic analytical tool that is used to calculate the short- and long-term effects of an event or disturbance on a system. This study used an impulse response function analysis that looks at CH_4 emissions in reaction to changes in GDP, LPI, and CPI across 30 periods. Each independent variable causes a shock, and Figure 6 illustrates how the shock affects CH_4 emissions. Positive trends are generally observed in the response of GDP, LPI, and CH_4 emissions themselves. It can be observed that during the course of the 30-year period, there is a correlation between rises in GDP and LPI and an increase in CH_4 emissions. A positive trend is seen in the way that CH_4 emissions react to changes on their own, indicating the cumulative impact of CH_4 emissions on themselves. On the other hand, even if the CPI responded positively for the first three years, it now has a negative impact on CH_4 emissions. This suggests that while an increase in the CPI may at first result in a rise in CH_4 emissions, over time the effect is likely to become negative. This aligns with the model, particularly with regard to the coefficients assigned to each variable.

At the start of the period, the reaction of CH_4 emissions to itself is 0.01; this indicates a 1% influence on CH4 itself. thereafter showed an increasing pattern, with a peak in the fifth period reaching 0.04, or a 4% influence on itself. The graph displays variations (ups and downs) in CH_4 emissions since the shock from periods 0 to 15. Accordingly, following a shock to itself, there is instability in CH_4 emissions for the first 15 years, and starting in year 16, there is stabilization.

Additionally, we can observe the response of CH_4 emissions over 30 time periods (years) following the GDP shock. As may be observed, until the sixth or seventh period following the shock, CH_4 emissions saw a significant spike—possibly the largest in the thirty years following the shock to GDP. After that, until the tenth period, the reaction of CH_4 emissions dropped. Throughout the year, these variations persist; but, in the 26th or 27th period, they start to decline and stabilize. This indicates that, during the 25 years following the GDP shock, CH_4 emissions have fluctuated, first showing a positive trend before eventually regaining equilibrium in their impact. Furthermore, a trend every ten years is evident, with an upward trend accompanied by an increase in the first five years and a decline in the next five, and so on. Accordingly, the influence of GDP on CH_4 emissions response is expected to exhibit a spike (rise) during the first half-decade, then decline but remain consistently positive over the next half-decade, and so on. Presumably, oscillations in the change of CH_4 emissions will occur for the first 25 years after an economic peak, such as a recession or monetary crisis, before stabilizing. But when compared to other variables, the variability in CH_4 emissions due to the GDP shock is substantially less. When other factors are taken into account, the shock brought on by GDP is still evident because there is a 10-year period of inconsistent CH_4 emission.

Analogous to the GDP impact, the LPI variable likewise exhibited varying trends that tended to rise until the fifteenth period, at which point a graph that continuously increased indicated a balanced response. The response of CH_4 emissions is found to be unstable up to the first 15 years following the shock induced by the LPI; following that time, there will be stability in the response of CH_4 emissions over the next years. After year 15, Figure 6 demonstrates that the response of CH_4 emissions to the LPI continuously rises to a relatively high level. It's possible that this is due to the irregular early-period CH_4 emissions from cattle, including milk, meat, fur, and manure. As time passes, these compounds' effects on CH_4 emissions, however, cause a steady increase. The long-term impact of the LPI on CH_4 emissions is likely to be positively significant.

Source: World Bank (2023), data processed

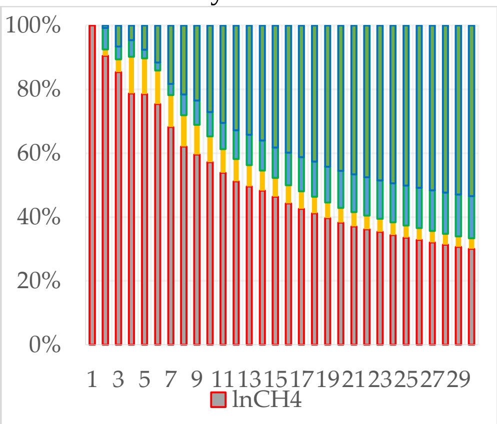
Figure 6. Impulse Response Function Graph for $lnCH_4$

Comparing the effects of the CPI shock with the other two independent variables yields different conclusions, as seen in Figure 6. Five years after the shock, the reaction of CH_4 emissions has tended to be unstable in its direction, either positive or negative, as evidenced by the variations at the 0 line seen in the first five periods. From then on, the variation stays negative until year 16, at which point it steadily declines as indicated by the graph. This indicates a 16-year negative duration for the instability brought on by CPI on CH_4 emissions. The stability of CH_4 was eventually overcome after 16 years, with a consistent deteriorating trend. Based on this finding, it is reasonable to expect that as the years go by, the CH_4 emissions' reaction to the shock brought on by the agriculture sector will continue to decline.

Variance Decomposition

Variance decomposition is used to calculate the amount of variability or fluctuation in a variable that can be attributable to variations in other variables in the system. This method helps to understand how each variable contributes differently to the variance of a specific variable across time. The variance decomposition distribution of endogenous variables on CH_4 emissions is displayed in Figure 7. The first period demonstrates that, with other factors not yet contributing to CH_4 emissions, the contribution of CH_4 emissions to its own variation is 100%. This suggests that, in the first year, pure CH_4 emissions occur without the influence of external factors. The contribution of other variables to the variation of CH_4 emissions begins to emerge in the second to fourth period, or the short-term period in this example. Of these variables, the CPI has the largest impact, aside from CH_4 emissions. The following period illustrates how the contribution of LPI begins to rise with the lengthening of the time. The LPI's contribution to the variance in CH_4 emissions is still higher than its own, even after the 20th era. This suggests that over the long run, the LPI has a greater influence on changes in CH_4 emissions than it does on changes in emissions alone. This demonstrates the LPI's significant long-term influence on CH_4 emissions. Conversely, while it peaks in the fourth period and then gradually declines in the subsequent periods, GDP's contribution to the variation of CH_4 emissions tends to be constant or steady. This suggests that the impact of GDP on variations in CH_4 emissions is constant over time and will progressively decline.

The following deductions can be made in light of the explanation given above: From the start of the era to the sixteenth period, CH_4 emission is the factor that contributes most to its own variance. 2) The LPI is the factor that contributes most to changes in CH_4 emissions after the 16th period, indicating that livestock has a major long-term influence on these changes. 3) While it makes up the smallest fraction of variations in CH_4 emissions relative to other variables, GDP tends to be steady over the long run.



Source: World Bank (2023), data processed

Figure 7. Stacked diagram of the distribution of variance decomposition of endogenous variables on CH_4

CONCLUSION

Based on the study's findings, a number of conclusions were drawn that were in line with its goals, including the following: there is a significant positive long-term relationship between economic growth and livestock production and methane emissions, or economic growth and livestock production raise methane emissions over time to the point where they are outside the parameters of the Environmental Kuznet Curver (EKC); there is also a significant short-term relationship between all variables and the value of methane emissions over time, or all variables—that is, methane emissions, economic growth, livestock production index, and crop production index—a particular period of time affect methane emissions themselves in a shorter amount of time. The Granger causality test demonstrates the substantial impact of agriculture and livestock on GDP, as well as the bidirectional relationship between GDP and CH_4 emissions. The various ways that methane emissions react to independent factors like GDP, the Livestock Production Index (LPI), and the Crop Production Index (CPI) are highlighted by the Impulse Response Function analysis. Moreover, the Livestock Production Index (LPI) has a greater influence on changes in CH_4 emissions beyond a specific time, indicating a substantial long-term impact of the livestock industry on methane emissions.

Based on the findings, we offer a number of recommendations for policies that promote sustainable and climate-friendly agriculture while taking into account the effects on the environment. These include incorporating measures to anticipate climate change into all tiers of national planning, development strategies, and sectoral policies; evaluating the impacts of climate change in all development projects; promoting climate education and awareness; and building capacity through training and capacity building programs to enhance knowledge and skills in the field of mitigation by involving relevant sector workers and stakeholders. The 13th SDG's objectives are addressed in a number of ways by the policies below.

Future research on the waste variable is suggested, as Climate Transparency reports that Indonesia's waste or waste sector is the country's largest source of methane emissions, accounting for 56% of all methane emissions in 2019. The most recent dataset can be used, as obtaining it was a challenge for our study. To obtain good modeling results, further recommendations could be to evaluate multiple time series methodologies. Because this research is constrained or generalized to the context of the entirety of Indonesia, it can then perform spatial analysis in specific Indonesian regions.

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