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The BVAR Model for Analyzing CO_2 Emissions on Renewable Energy, Economic Growth, and Forest Area

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Abstract

This research investigates the management of CO_2 emissions, a significant factor in the climate change phenomenon, focusing on Indonesia. The objective is to examine the correlation between CO_2 emissions and their causal variables: economic growth (measured by gross domestic product), forest area, and renewable energy (RE) consumption. The Bayesian vector autoregressive (BVAR) model was employed to address the complexity of multivariate interactions and overcome limitations associated with small datasets. The analysis revealed that economic growth and reduced forest area significantly contributed to high CO_2 emissions, while renewable energy consumption exhibited a mitigating effect. The BVAR model demonstrated substantial predictive accuracy, highlighting its suitability for analyzing environmental and economic data in resource-constrained scenarios. These findings emphasize the critical need for targeted policy actions in Indonesia, including safeguarding forest areas, addressing illegal logging and burning, and accelerating the transition to renewable energy. The study provides a novel application of the BVAR model in environmental research, showcasing its potential for generating actionable insights into emissions management. This study contributes to the understanding of sustainable development by proposing an innovative way to support evidence-based policies that reduce CO_2 emissions as well as mitigate climate change impacts.

Keywords:

Carbon Dioxide;
Gross Domestic Product;
Forest Area;
Renewable Energy;
Bayesian Vector Autoregressive.

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1- Introduction

High carbon dioxide (CO_2) emissions are the main factors in global climate change, particularly by forming a layer in the atmosphere to trap heat energy and cause global warming [1]. In 2020, data from the Joint Research Center (JRC) showed that greenhouse gas emissions increased significantly, with carbon dioxide contributing 71.6% [2]. This condition requires immediate action to prevent the negative impacts from the climate change phenomenon on the population, economy, technology, and natural energy [3].

Several problems related to carbon dioxide emissions have gained significant attention across various sectors, including building, transportation, economic, and political. The building sector is estimated to contribute approximately half of the carbon dioxide emissions linked to global energy use [4]. This evaluation was conducted using univariate and multivariate model and different feature extraction methods in various regions, including the United Kingdom, Brazil, the United States, India, South Africa, China, the world average, and the European Union. The analysis used machine

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learning methods, such as linear regression, autoregressive (AR) and moving average models, Shallow neural networks, and artificial neural networks. Despite these efforts, integrated approaches that account for multiple dynamic factors remain limited. In the transportation sector, research conducted using the approximation of deep learning process with capturing long-term dependencies within sequential data shows that vehicle speed, road gradient, and acceleration have a significant effect and positive correlation with the rate of carbon dioxide emissions [5]. However, studies often overlook how transportation dynamics interact with broader economic or environmental factors. Similarly, the economic sector analyzed the relationship between CO_2 emissions and inflation from 189 countries from 1970 to 2020 [6]. The results show a significant but weak negative relationship between core inflation and carbon dioxide emissions per capita, indicating the need for additional policies to achieve substantial reduction. In the political sector, research examines the effects of democracy, corruption, economic growth, and information as well as communication technology on carbon dioxide emissions in Sub-Saharan African countries. The results show that the significant effect of democracy and economic growth while corruption and the foreign direct investment (FDI), as key driver of globalization and economic integration, enabling resource sharing, technological advancement, and global economic interdependence, have a more complex impact and depend on the local context [7]. These findings reveal a critical gap in understanding how these multifaceted factors influence CO_2 emissions on a broader scale.

The reduction of risks caused by increasing carbon dioxide levels is a long-term goal, which is affected by global economic growth. Research in East Africa shows that economic growth, population, and renewable energy consumption have different effects on carbon emissions in each region [8]. A similar trend was observed in China, where renewable energy significantly reduced air pollution, despite the reliance on non-renewable energy sources like fossil fuels, the economic sector remains predominantly influenced by them [9, 10]. Wavelet analysis was utilized as well to find out the influences of economic activities on CO_2 emissions in China, even including in renewable or non-renewable energy consumption. The outcomes show that the causal relationship between variables have significant changes in the lead-lag pattern. Economic globalization has had difference between short-term and long-term effects on CO_2 emissions as a result of the implementation of economic growth, renewable or nonrenewable energy sources. However, these studies lack a comprehensive framework integrating renewable energy, and environmental variables in regions, such as Indonesia.

This study employs a Bayesian vector autoregressive (BVAR) model to address these gaps, effectively capturing dynamic causal relationships among endogenous variables. Unlike traditional VAR models, which are prone to over-parameterization with limited data, the BVAR model incorporates Bayesian methods and advanced sampling techniques such as the Markov Chain Monte Carlo algorithm to improve efficiency and accuracy [11, 12]. This approach provides a novel framework for analyzing the linkage between the renewable energy consumption, economic growth, forest area, and CO_2 emissions. This study aims to offer insights into sustainable policies that make economic activities and environmental conservation in Indonesia be stable.

2- Literature Review

Several studies have been conducted in recent years to investigate carbon dioxide emissions, including research on the effect of urbanization and economic activity in achieving net zero carbon. This study used a vector error correction model (VECM) to determine long-term and short-term interactions, indicating a unidirectional causality from urbanization, exports, economic growth, and FDI to CO_2 emissions in the short term [13]. Another study investigates the role of urbanization and economic activity in reaching net zero carbon. One well-known study looked into the impact of urbanization and economic activity on achieving net-zero carbon emissions, utilizing a vector error correction model (VECM) to identify long-term and short-term trends. The data revealed a short-term unidirectional causal association between urbanization, economic growth, exports, foreign direct investment (FDI), and CO_2 emissions [14]. A study examined the roles of renewable energy consumption, technological innovation, and forest areas in advancing green development in Indonesia, employing a dynamic ordinary least squares (OLS) model. The findings show that renewable energy consumption, economic growth, and technological innovation have a significant impact on CO_2 emissions [15]. Furthermore, advanced deep-learning techniques have shown that CO_2 emissions maintain a long-term statistical relationship with electricity consumption and GDP [16].

Research on carbon dioxide emissions using time series analysis has gained significant attention, which can be used to determine relationship between variables. For instance, a time series analysis examining sector growth and its impact on carbon dioxide emissions in Pakistan showed a positive and significant relationship between industrial development, population density, and their respective contributions to carbon dioxide emissions [17]. Another instance, a study on sectoral growth in Pakistan revealed a positive and significant relationship between industrial development, population density, and their contributions to CO_2 emissions [18]. Similar research used time series analysis to determine whether carbon dioxide emissions and energy consumption could determine economic performance in South Korea. Several time series models, such as AR distributed lag, dynamic OLS, and fully modified OLS, showed that carbon dioxide emissions triggered economic growth in South Korea [19]. Beyond environmental applications, time series models have also been used in public health and security, such as analyzing the effects of COVID-19 on crime rates in New York City [20] and classification breast cancer [21].

One of the time series model widely used for the analysis of a multivariate problem is the VAR model. In economics field, the impact of the macroeconomic on oil price shocks can be shown using VAR models [22]. In the atmospheric field, the VAR model predicts rainfall from various regions by considering natural phenomena such as Central Equatorial Indian Ocean (CENS) and the Madden-Julian Oscillation (MJO) [23]. Previous research has explored the effect of government spending shocks on consumption of macroeconomic factors such as inflation, interest rates, and other factors in Indonesia [24] and America [25]. The results showed that government spending shocks after the pandemic affected increased economic activity. Bayesian method combined with the VAR model was used to overcome over-parameterization and small datasets, showing that government spending shocks could stabilize unstable macroeconomic forces post-pandemic. A similar case was also carried out to determine whether the digital economy has an effect towards to green energy after COVID-19 phenomenon [26], predict how the growth of gross domestic product (GDP), and simulate financial risk scenarios in Brazil [27]. Another investigation was carried out using Bayesian hierarchical AR vector model to analyze microbial dynamics in a wastewater treatment facility, providing insight into the interactions between microbial communities in complex environmental systems [28].

The VAR model can use the Granger causality test to analyze the relationship between GDP and energy consumption in Ecuador [29], and also to examine relationship between transport structure adjustment, energy intensity, and CO_2 emissions in the Yangtze River Delta [30]. The results show the causal relationship between energy intensity and CO_2 emissions, providing an important perspective for government policy in the transportation sector. Furthermore, the role of BVAR model was investigated in real-time nowcasting of US economic activity, which successfully handled big data challenges such as volume, variety, and velocity [31]. The seasonal BVAR (SBVAR) model was also used to identify the effect of exchange rate movements on the Mongolian economy, showing significant effects through trade and financial channels [32]. Based on recent developments such as large Bayesian VARS using stochastic volatility, the VAR model and variations are increasingly efficient in empirical macroeconomic analysis, offering speed and accuracy in estimating the observations' value [33].

3- Research Method

3-1- Data Source

This research used annual data accessed through The World Bank website, www.worldbank.org, and EDGAR – Emissions Database for Global Atmosphere, https://edgar.jrc.ec.europa.eu/, from 1990 to 2022.

3-2- Operational Variables

This research used 4 datasets in Indonesia, namely CO_2 emissions, GDP, renewable energy consumption, and forest area. Each variable consisted of 33 annual data that were collected from 1990 to 2022.

3-3- The Analysis Process

The analysis process of Bayesian Vector Autoregressive Model can be shown as a flowchart in the following Figure 1.

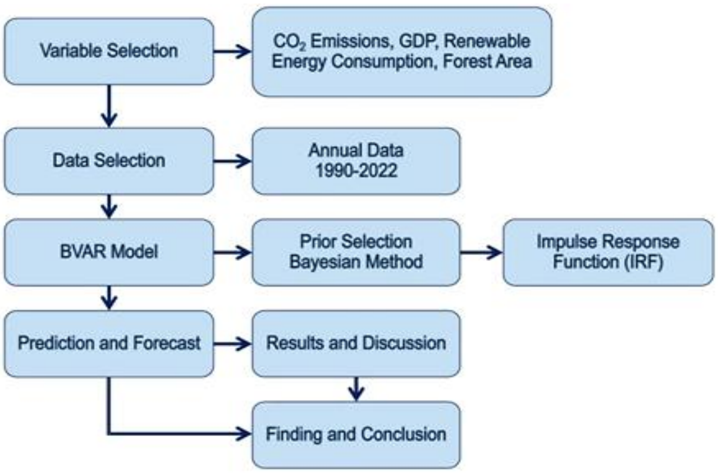

Figure 1. Analysis process of the BVAR model

Figure 1 illustrates the process of analyzing the relationship between economic growth, renewable energy consumption, and forest area on CO_2 emissions in Indonesia using Bayesian VAR. The annual data of each variable are all used as input to the Bayesian VAR model. In order to use this Bayesian VAR model, one must first determine the prior that will be used to assist in the parameter estimation process in the model. In this study, Minnesota priors are used because of their ease of computation and implementation. Then with this prior, a Bayesian VAR model of economic growth, forest area, and renewable energy consumption against CO_2 emissions is formed. Then the impulse response function of the model will be analyzed to determine the impact of the independent variable when receiving a shock from the dependent variable. Then, the Bayesian VAR model formed will be used for prediction, and the residuals will be analyzed to see if the model is close to the actual data. Finally, conclusions are drawn from the process that has been carried out.

3-4- VAR Model

The VAR model was used for multivariate time series analysis based on the dependency relationship between lag and all variables. This model was determined by regressing all variables against their lag and the related lag until the maximum level p, expressed as VAR(p) [29].

The VAR model served as a generalization of the AR, where all variables were assumed to be endogenous, showing the interrelation between other variables. Moreover, the VAR model with lag p [7] could be stated as follows:

$$Y_t = A_0 + A_1 Y_{t-1} + \cdots + A_p Y_{t-p} \tag{1}$$

or

$$A_p(B) Y_t = A_0 + e_t \tag{2}$$

where Y_t is stationary $M \times 1$ vector, for $t = 1,2,\ldots,M$,A_p is an $M \times M$ coefficient matrix, and B is the lag operator. The vector e_t is an $M \times 1$ a residual vector or a white noise vector of dimension M, $VWN(0, \Sigma)$, and

$$A_p(B) = 1 - A_1 B - A_2 B^2 - \cdots - A_p B^p. \tag{3}$$

3-5- The Bayesian VAR Model

The VAR model is commonly used in the macroeconomic forecasting and policy research, particularly for exploring the existence of causal effects among multiple variables. To establish the importance of causation between variables and verify the usefulness of one variable to predict another, Granger causality is needed. However, the number of dimensional models often leads to inaccuracy caused by each dataset, particularly when there is over-parameterization. In recent years, big data has affected model accuracy, as many datasets cannot be recorded sequentially, leading to partial fit of the model. To address these challenges, Bayesian method is preferred to show efficiency in dealing with multiclass problems [34]. By integrating Bayesian method with VAR model, the limitations of high-dimensional data can be mitigated through the use of informative conjugate prior, which can effectively reduce data dimensionality. Bayesian framework allows consideration of a broad spectrum of monetary problems, requires prior information and can report multi-layered uncertainties through hierarchical modeling [35].

This study is grounded in the theory that economic, environmental, and energy factors are interdependent and dynamically influence CO_2 emissions. In general, economic growth is measured by gross domestic product (GDP) and is often linked to increased energy consumption and environmental degradation. Simultaneously, renewable energy and forest areas serve as mitigating factors in controlling emissions. These relationships form a complex, dynamic system where each variable interacts with the others over time. In capturing these interactions, this study employs the Bayesian vector autoregressive (BVAR) model, a robust extension of the traditional vector autoregressive (VAR) framework. The VAR model is widely used in econometrics to analyze the dynamic relationships between multiple endogenous variables. However, its reliance on large datasets often leads to over-parameterization and inefficiencies, especially when data availability is limited. This limitation is particularly relevant for studies in developing countries or regions with sparse historical data, like Indonesia.

The incorporation of Bayesian methods addresses these shortcomings by applying prior distributions to model parameters. This approach enhances estimation efficiency and reduces overfitting. By using the Markov Chain Monte Carlo (MCMC) algorithm, the BVAR model generates posterior distributions for parameters, allowing for a probabilistic understanding of the relationship between variables. This probabilistic framework is particularly advantageous in environmental studies, where uncertainties and variability are inherent.

VAR model is commonly used to solve economic problems, including forecasting. However, some challenges are often faced in selecting more important indicators due to the problem of excessive parameterization [36]. This is because excessive parameterization can cause many dimensional models leading to inaccurate on each dataset. Therefore, Bayesian method was preferred due to the ability to efficiently handle multivariate problems, particularly on small datasets [34].

Bayesian method provides a framework for incorporating data into estimation and inference. By obtaining the posterior distribution, the VAR model could be adjusted into a multivariate regression model. Suppose $\boldsymbol{Y} = [Y_1, Y_2, \dots, Y_T]$, $\boldsymbol{A} = [A_0, A_1, \dots, A_p]$, $\boldsymbol{e} = [e_1, e_2, \dots, e_T]$ and $\boldsymbol{X} = [X_0, X_1, \dots, X_{T-1}]$, with $\boldsymbol{X}_{t-1} = [1, Y_{t-1}, Y_{t-2}, \dots, Y_{t-p}]^T$ hence the VAR(p) model with K dimensions and normal distribution [7], could be rewritten as:

$$Y_t = A_t^T X_t + e_t \tag{4}$$

or could be written in matrix form as:

$$Y = \boldsymbol{XA} + \boldsymbol{e} \tag{5}$$

In general, Bayesian method was defined as follows:

$$p(Y, Y_{t-p}, \cdots, Y_0 | \boldsymbol{A}, \boldsymbol{\Sigma}) = \left(p(Y_T | Y_{T-1}, \cdots, Y_{T-p} | \boldsymbol{A}, \boldsymbol{\Sigma}) \cdots (Y_1, Y_0, \cdots, Y_{-p} | \boldsymbol{A}, \boldsymbol{\Sigma})\right) . \left(p(Y_0, \cdots, Y_{-p} | \boldsymbol{A}, \boldsymbol{\Sigma})\right) \tag{6}$$

where

$$p(Y_t | \mathrm{X_t}, \boldsymbol{A}, \boldsymbol{\Sigma}) = \frac{1}{(2\pi)^{\frac{m}{2}}} |\Sigma|^{-\frac{1}{2}} \exp\left[-\frac{1}{2}(Y_t - \boldsymbol{A}^T X_t)^T \boldsymbol{\Sigma}^{-1} (Y_t - \boldsymbol{A}^T X_t)\right] \tag{7}$$

or for $\boldsymbol{Y} = [Y_1, Y_2, \dots, Y_T]$ and $(Y_t - \boldsymbol{A}^T X_t)^T \boldsymbol{\Sigma}^{-1} (Y_t - \boldsymbol{A}^T X_t) = tr(\Sigma^{-1} \sum_{t=1}^{T} (Y_t - \boldsymbol{A}^T X_t)(Y_t - \boldsymbol{A}^T X_t)^T)$, then the likelihood function $L(Y | \boldsymbol{A}, \boldsymbol{\Sigma})$ could be given by:

$$\begin{aligned} L(Y | \boldsymbol{A}, \boldsymbol{\Sigma}) &= p(Y | \boldsymbol{A}, \boldsymbol{\Sigma}) \\ &= \frac{1}{(2\pi)^{\frac{Tm}{2}}} |\boldsymbol{\Sigma}|^{-\frac{T}{2}} \exp\left[-\frac{1}{2} tr\left(\boldsymbol{\Sigma}^{-1} \textstyle\sum_{t=1}^{T} (Y_t - \boldsymbol{A}^T X_t)(Y_t - X_t^T \boldsymbol{A})\right)\right] \\ &= \frac{1}{(2\pi)^{\frac{Tm}{2}}} |\boldsymbol{\Sigma}|^{-\frac{T}{2}} \exp\left[-\frac{1}{2} tr\left(\boldsymbol{\Sigma}^{-1} \textstyle\sum_{t=1}^{T} (Y_t - \boldsymbol{A}^T X_t)(Y_t - \boldsymbol{A}^T X_t)^T\right)\right] \\ &= \frac{1}{(2\pi)^{\frac{Tm}{2}}} |\boldsymbol{\Sigma}|^{-\frac{T}{2}} \exp\left[-\frac{1}{2} tr\left(\boldsymbol{\Sigma}^{-1} (\boldsymbol{Y} - \boldsymbol{XA})^T (\boldsymbol{Y} - \boldsymbol{XA})\right)\right] \end{aligned} \tag{8}$$

Subsequently, by substituting the prior and likelihood functions, the posterior could be defined as follows:

$$p(\boldsymbol{Y}, \boldsymbol{\Sigma}, \boldsymbol{A}) = p(\boldsymbol{A}, \boldsymbol{\Sigma} | Y) . p(\boldsymbol{Y}) = p(\boldsymbol{A}, \boldsymbol{\Sigma}) . \mathrm{L}(Y | \boldsymbol{A}, \boldsymbol{\Sigma}) \tag{9}$$

Hence, it could be obtained:

$$p(\boldsymbol{A}, \boldsymbol{\Sigma} | Y) = p(\boldsymbol{A}, \boldsymbol{\Sigma}) . \frac{\mathrm{L}(Y | \boldsymbol{A}, \boldsymbol{\Sigma})}{\mathrm{p}(Y)} \propto \mathrm{L}(Y | \boldsymbol{A}, \boldsymbol{\Sigma}) . p(\boldsymbol{A}, \boldsymbol{\Sigma}) \tag{10}$$

where $\mathrm{p}(\mathbf{A}, \boldsymbol{\Sigma} | \mathrm{Y})$ was the posterior, $\mathrm{L}(\mathrm{Y} | \mathbf{A}, \boldsymbol{\Sigma})$ was the likelihood, and $\mathrm{p}(\mathbf{A}, \boldsymbol{\Sigma})$ was the prior. Therefore, it could be expressed in the equation:

$$\begin{aligned} p(\boldsymbol{A}, \boldsymbol{\Sigma} | Y) &\propto \mathrm{L}(Y | \boldsymbol{A}, \boldsymbol{\Sigma}) . p(\boldsymbol{A}, \boldsymbol{\Sigma}) \\ &= \frac{1}{(2\pi)^{\frac{Tm}{2}}} |\Sigma|^{-\frac{T}{2}} \times \exp\left[-\frac{1}{2} tr\left(\boldsymbol{\Sigma}^{-1} \widehat{\boldsymbol{S}}\right)\right] \times \exp\left[-\frac{1}{2}(\boldsymbol{A} - \widehat{\boldsymbol{A}})^T (\boldsymbol{\Sigma} \otimes (\boldsymbol{X}^T \boldsymbol{X})^{-1})^{-1} (\boldsymbol{A} - \widehat{\boldsymbol{A}})\right] \mathrm{p}(\mathbf{A}, \boldsymbol{\Sigma}) \end{aligned} \tag{11}$$

where $\widehat{\boldsymbol{S}} \equiv (\boldsymbol{Y} - \boldsymbol{XA})^{\boldsymbol{T}} (\boldsymbol{Y} - \boldsymbol{XA})$, $\widehat{\boldsymbol{A}} \equiv (\boldsymbol{X}^{\boldsymbol{T}} \boldsymbol{X})^{-\mathbf{1}} \boldsymbol{X}^{\boldsymbol{T}} \boldsymbol{Y}$, dan $\boldsymbol{A} \sim \boldsymbol{N}(\widehat{\boldsymbol{A}}, \boldsymbol{\Sigma} \otimes (\boldsymbol{X}^{\boldsymbol{T}} \boldsymbol{X})^{-\mathbf{1}})$.

3-6- Prior Specification

Bayesian method plays a major role in research with small samples, namely power and bias parameters. These two aspects are related to analyzing the sensitivity of prior specifications [7]. In this research, Bayesian method and the VAR model were combined by selecting Minnesota as the prior due to simple implementation and calculation. These prior stated that each variable would follow a random pattern, thereby explaining the movement of most of the time series data [19]. For the VAR model with order p, the Minnesota prior stated that the significance of the variables was normally distributed, namely $A_i \sim N(\bar{A}_i, \sigma_{A_i}^2)$, for $i = 1,2, \cdots, p$ and the prior expected value of A_i at the first lag of the dependent variable was equal to one, $\bar{A}_1 = I_n$, and at other lags, the prior expected value was zero, where $\bar{A}_2 = \bar{A}_3 = \cdots = \bar{A}_p = 0_n$, and the variance of A_i for $i = 1,2, \cdots, p$ was given as follows:

$$\sigma_{A_i}^2 = \frac{\lambda^2}{i^2}\begin{bmatrix} 1 & \beta\frac{\hat{\sigma}_1^2}{\hat{\sigma}_2^2} & \cdots & \beta\frac{\hat{\sigma}_1^2}{\hat{\sigma}_n^2} \\ \beta\frac{\hat{\sigma}_2^2}{\hat{\sigma}_1^2} & 1 & \cdots & \beta\frac{\hat{\sigma}_2^2}{\hat{\sigma}_n^2} \\ \vdots & \vdots & \ddots & \vdots \\ \beta\frac{\hat{\sigma}_n^2}{\hat{\sigma}_1^2} & \beta\frac{\hat{\sigma}_n^2}{\hat{\sigma}_2^2} & \cdots & 1 \end{bmatrix} \tag{12}$$

where β was a value that governed the decay of the variance value with the expansion of the lag order and handled the relative tightness of the prior variance. This varied significantly compared to the prior variance in other lags within a specific equation, particularly in relation to the lag itself $(0 < \beta < 1)$ and $\Sigma = diag(\hat{\sigma}_1^2, \hat{\sigma}_2^2, \cdots, \hat{\sigma}_n^2)$.

In Minnesota priority, BVAR model is frequently used with the parameter λ playing a crucial role in determining the degree of shrinkage applied to the regression coefficients by controlling the prior beliefs about the model structure. Specifically, λ controls the shrinkage of the priors to a certain value (usually zero) for the other variables coefficient in the VAR system. This parameter controls the extent to which coefficients for variables different from the target variable are shrunk to their initial values, which were often zero. When λ = 0, it shows full confidence that the coefficients are zero (full shrinkage), and λ > 0 indicates a lower degree of confidence. The parameter λ acts as a shrinkage controller in Bayesian process, adjusting how much or little the regression coefficients are allowed to differ from zero. The prior density function (PDF) in the Minnesota Prior generally shrinks the coefficients of the other variables in the system toward zero. This shows that the variables have no significant effect on the target unless there is strong evidence in the data to suggest otherwise. The parameter λ controls how strongly this shrinkage occurs. A large value of λ allows the coefficients to fluctuate more freely as shown in the data, while a small value of λ strengthens indicates approaching zero. The standard deviation of the prior λ controls the stringency or weighs the relative significance of the prior and the data. For $\lambda \to 0$, the prior is strictly allowed to apply, while for $\lambda \to \infty$, the posterior estimation considers OLS estimation.

In this study, the MCMC algorithm was employed to estimate the posterior distribution and generate additional data using the Markov chain process. This method produced an extended set of random variables based on the Markov chain. However, the parameter vector samples were serially dependent rather than independent. To validate these samples for posterior inference, the law of large numbers and the central limit theorem for dependent samples were applied. It was observed that the precision of the approximation for the desired posterior moments was lower when using dependent samples, indicating the need for larger sample sizes to achieve reliable inference, especially when dealing with smaller datasets. Despite the considerable computational cost, the MCMC method has gained popularity due to its computational simplicity and efficiency. Consequently, obtaining Bayesian posterior models was complex and required an integration process, emphasizing the need for alternative numerical methods to calculate the posterior marginal of a parameter [24]. The BVAR (Bayesian Vector Autoregression) model showed good performance with a small dataset, but there were some limitations due to the size of the data. A small dataset can restrict ability of model in capturing the complex relationships between variables and then in increasing the risk of overfitting, especially when the number of model parameters is higher than the available data. Larger datasets, however, can improve the results because they provide more information for accurately estimating parameters, which can enhance the robustness of the model and reduce overfitting. While a larger dataset can lead to a more stable and generalizable model, it also presents challenges such as increased model complexity and higher computational demands, particularly when using methods like Metropolis-Hastings or Gibbs sampling. Thus, although larger datasets can improve the reliability and robustness of the model, adequate computational resources are required to ensure efficient analysis without sacrificing accuracy.

4- Results and Discussion

4-1- Data Preparation

This research used four variables namely, carbon dioxide emissions, gross domestic product (GDP), renewable energy consumption, and forest area. Each variable comprised 33 data points, covering the period from 1990 to 2022, as shown in Figure 2.

Based on Figure 2, it is evident that Indonesia experienced significant economic growth from 1990 to 2022, as reflected in the consistent increase in GDP over the years. However, this economic growth coincides with a rise in CO_2 emissions, indicating that industrialization and economic activities have likely contributed to increased environmental pressures. Conversely, the ratio between renewable energy consumption and the total energy mix has steadily declined during the same period. It suggests a decreasing reliance on renewable energy sources, which could hinder the country's efforts toward achieving sustainable development and reducing its carbon footprint.

Additionally, the forest area as a percentage of total land area has continuously declined, implying substantial deforestation over the years. This trend highlights concerns about the loss of biodiversity, disruption of ecosystems, and the reduction of carbon sequestration capacity. The overall patterns underscore a critical challenge for Indonesia: while economic growth has been robust, it has been accompanied by environmental trade-offs. Policymakers need to prioritize strategies that promote renewable energy use and forest conservation to ensure sustainable development in the future.

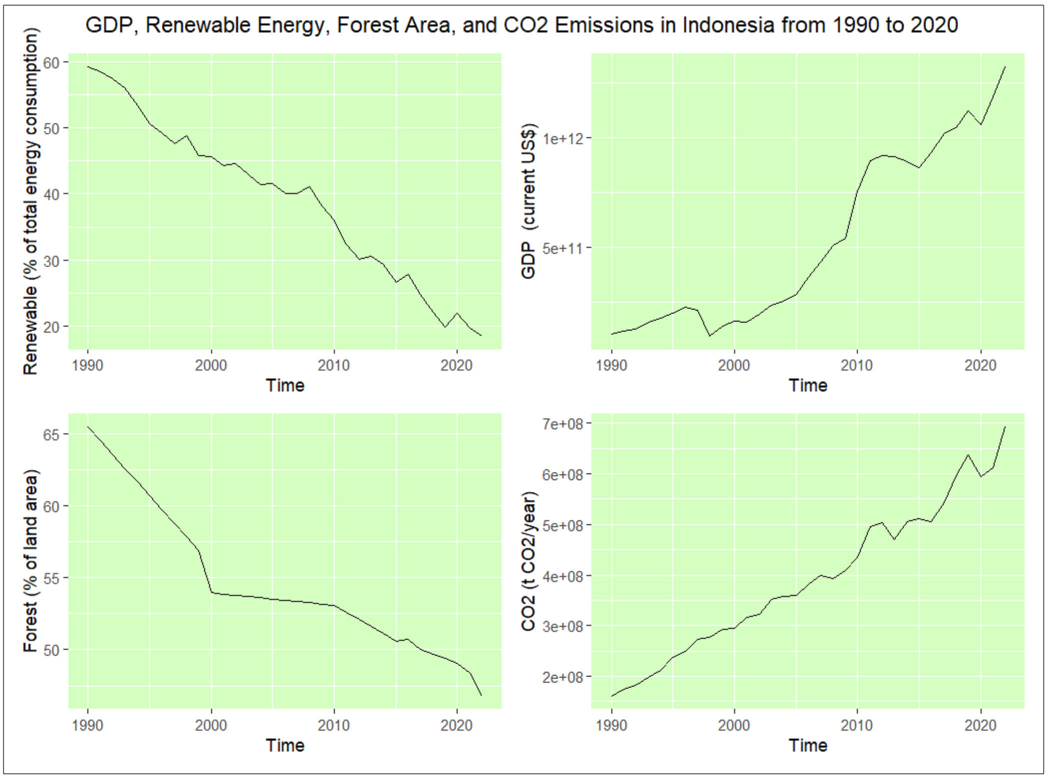

Figure 2. **Data GDP, renewable energy consumption, forest area, and carbon dioxide**

4-2- Priors for Bayesian VAR Model

After preparing the data, the next step involved specifying the priors and constructing the model. In this study, Minnesota priors were applied with a hierarchical approach to the lambda (λ) hyperparameter. Figure 3 illustrates the trace and probability density functions of the lambda hyperparameter.

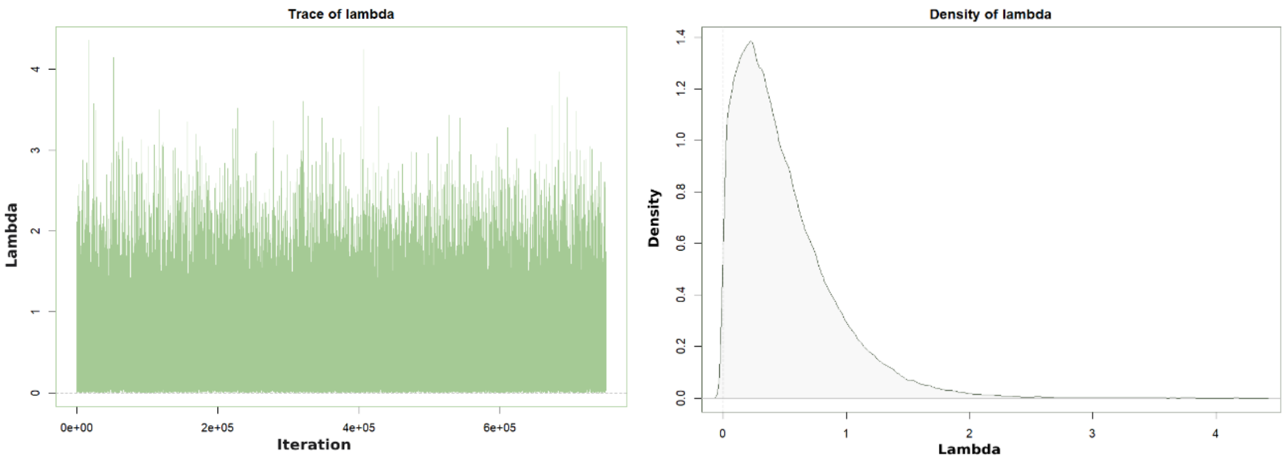

Figure 3. **Trace and Density Plot of λ Hyperparameters**

As presented in Figure 3, the Minnesota prior allows all independent variables to follow a random pattern and fits the results that are specifications with good performance, showing potential to be used in the built Bayesian VAR model. The interpretation of the trace and density plot of parameter λ using the Minnesota Prior is as follows. First, the trace plot shows the change in the value of λ during iterations in the sampling process, showing constant fluctuation between approximately 0 and 3 throughout 10,000 iterations. This shows that no particular trend shows slow convergence or bias in sampling, suggesting proper process and wide distribution of λ. The consistent and rapid fluctuation of λ from one iteration to another shows that the model is flexible enough to shrink the regression coefficients in accordance with the evidence in the data.

The density plot shows the posterior distribution of λ after the sampling process, suggesting the confidence of the model in certain values. Based on the results, the value of λ most often appears around 0.5-1.0, with a density peak of 0.5. This shows that most samples imply a moderate level of shrinkage towards zero for the coefficients of other variables in the VAR system. The density distribution decreases gradually above 1, and there is no probability of mass at 2.5. This shows that the model tends to have small coefficients. Since λ > 0 for most iterations, the model allows some flexibility in letting the coefficients move away from zero but with stronger confidence in shrinking towards small values or zero. Therefore, λ values distributed around 0.5-1 show that the model regulates the coefficient shrinkage towards small values or zero, allowing considerable flexibility based on the data. The shrinkage is not excessively strong ($\lambda \neq 0$) but still significant enough, suggesting that the model prioritizes small coefficients unless the data provides strong evidence to the contrary. The λ value is not completely close to zero but shows moderate shrinkage, where the model allows larger coefficients. However, it still tends to shrink the coefficients to small values. Based on the density plot and trace plot, λ value is close to zero for some iterations.

Based on Equation (12), the value of $\lambda \to 0$ shows that the variance of A_i for $i = 1,2,\cdots,p$ becomes smaller. A small variance shows that the estimated VAR regression coefficients are relatively stable. This shows that the estimated coefficient values based on the data have little variation and the model is stable. The result also shows a strong shrinkage of the BVAR model prior, thereby the coefficients will approach zero.

4-3- Impulse Response Function

Impulse Response Function (IRF) describes shock of all variables in the model, showing the dynamic structure of the BVAR model by explaining how each variable responds to shock over time. Therefore, IRF is used to determine the independent variables effects when receiving shocks from dependent variables. IRF of each variable is shown in Figure 4.

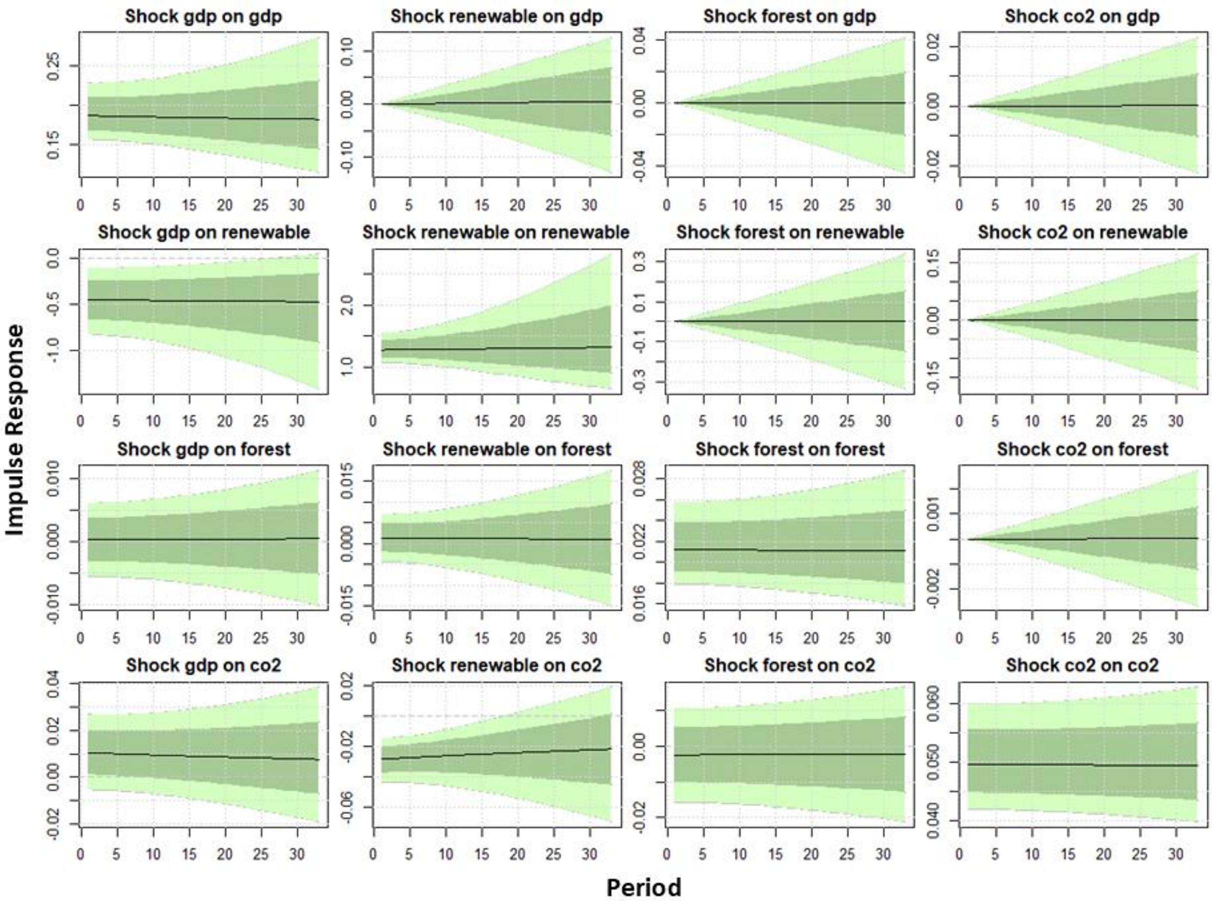

Figure 4. **Impulse Response Function**

As shown in Figure 4, the response of each variable has an approximately stable range in the dark green area, which is 68% credibility. In the lighter area, it shows a 95% confidence interval, the response of each variable has a high range for a sustained period. The graph shows the response for over 30 periods, namely years or quarters. Although the negative response appears persistent and long-lasting, its strength gradually decreases. The response (thick black) is below the zero line for most of the time horizon. This shows that when there is shock to GDP, the response of renewable energy consumption is negative. Therefore, GDP growth reduces the renewable energy consumption in the observed period. A GDP shock tends to reduce the renewable energy consumption, which appears significant in the initial period after the shock. This shows that when there is a sudden increase in GDP, economy's focus shifts from renewable energy consumption to less environmentally friendly alternatives. The interpretation suggests that GDP shock has a negative effect on renewable energy consumption over the observed period.

The interpretation of each IRF in Figure 4 shows significant consideration of shock of other variables to GDP. In the GDP variable, shock positively responds to GDP, with a substantial increase in stimulating growth. The response increases over time and appears statistically significant. In renewable energy consumption variable, the shock shows a small and positive response to GDP. However, the effect is relatively weak and the confidence interval narrows over time, showing high uncertainty and potential insignificance. In forest area variable, shock has minimal effect on GDP. The response is around zero with a wide confidence interval, showing an insignificant effect. In carbon dioxide emissions variable, shock has a very small response to GDP, with high uncertainty, showing an unclear relationship.

GDP shock has a significant negative effect on renewable energy consumption, showing that economic growth tends to reduce renewable energy consumption. In renewable energy consumption variable, the shock to renewable energy consumption produces a positive response that lasts. The result shows that renewable energy consumption system is self-reinforcing, suggesting a corresponding increase in consumption. In forest area variable, shock has a small negative impact on renewable energy consumption, although the confidence interval suggests non-statistical significance. Carbon dioxide emissions shock has a weak negative response to renewable energy consumption, showing that there is an unclear relationship between both variables.

Regarding forest area, GDP gives a small positive response, showing a relatively weak association with economic improvements. In renewable energy consumption variable, a negative effect is observed due to potential land use conflicts, such as biofuels. In forest area variable, the shock to forest area produces a strong and sustained positive response, showing stability in forest management. The shock to CO_2 emissions has a very small negative effect on forest area, with confidence interval around zero showing non-statistical.

Regarding CO_2 emissions, GDP shock shows a small positive response to CO_2 emissions that is indicating a significant association between both variables. However, the effect observed is small and not statistically significant. In renewable energy consumption variable, shock negatively affects CO_2 emissions. This shows that increasing the use of renewable energy consumption slightly reduces CO_2 emissions. In forest area variable, shock produces a small negative response, showing that increasing forest area can contribute to reducing CO_2 emissions. Shock positively and significantly affects CO_2 emissions, showing a continuous and stronger response.

Therefore, GDP has a negative effect on renewable energy consumption, as well as small influence on forest area and CO_2 emissions. Renewable energy consumption has a self-reinforcing effect but is not very significant regarding GDP and forest area. Furthermore, forest area tends to be stable to internal shocks, showing a negative relationship with renewable energy consumption. CO_2 emissions seem less affected by other variables, except renewable energy consumption, and naturally show a positive effect.

4-4- Model Bayesian VAR

In this research, Bayesian VAR model with lag 1 or BVAR(1) was formed with GDP as variable X1, renewable energy consumption as X2, forest area as X3, and carbon dioxide emissions as X4. Based on Equation (5), the BVAR(1) model that can be formed is as follows:

$$\begin{bmatrix} \log X1_t \\ X2_t \\ X3_t \\ \log X4_t \end{bmatrix} = \begin{bmatrix} A_{10} \\ A_{20} \\ A_{30} \\ A_{40} \end{bmatrix} + \begin{bmatrix} A_{11} & A_{12} & A_{13} & A_{14} \\ A_{21} & A_{22} & A_{23} & A_{24} \\ A_{31} & A_{32} & A_{33} & A_{34} \\ A_{41} & A_{42} & A_{43} & A_{44} \end{bmatrix} \begin{bmatrix} \log X1_{t-1} \\ X2_{t-1} \\ X3_{t-1} \\ \log X4_{t-1} \end{bmatrix} + \begin{bmatrix} e_{1t} \\ e_{2t} \\ e_{3t} \\ e_{4t} \end{bmatrix}$$
$$= \begin{bmatrix} 0.082 \\ -1.165 \\ -0.428 \\ 0.035 \end{bmatrix} + \begin{bmatrix} 1.000 & -0.003 & 0.001 & 0.000 \\ 0.000 & 1.000 & -0.002 & 0.000 \\ 0.000 & 0.001 & 0.998 & 0.000 \\ 0.000 & -0.001 & 0.001 & 1.000 \end{bmatrix} \begin{bmatrix} \log X1_{t-1} \\ X2_{t-1} \\ X3_{t-1} \\ \log X4_{t-1} \end{bmatrix} + \begin{bmatrix} e_{1t} \\ e_{2t} \\ e_{3t} \\ e_{4t} \end{bmatrix} \tag{13}$$

with the variance-covariance matrix value of the BVAR(1) model in the posterior can be calculated, hence it can be obtained

$$\mathbf{\Sigma} = \begin{bmatrix} 0.035 & -0.082 & 0.004 & 0.002 \\ -0.082 & 1.847 & 0.066 & -0.041 \\ 0.004 & 0.066 & 0.303 & -0.004 \\ 0.002 & -0.041 & -0.004 & 0.004 \end{bmatrix} \tag{14}$$

where $B\log X1_t = \log X1_t - \log X1_{t-1}$, $BX2_t = X2_t - X2_{t-1}$, $BX3_t = X3_t - X3_{t-1}$, $B\log X4_t = \log X4_t - \log X4_{t-1}$, $B\log X1_{t-1} = \log X1_{t-1} - \log X1_{t-2}$, $BX2_{t-1} = X2_{t-1} - X2_{t-2}$, $BX3_{t-1} = X3_{t-1} - X3_{t-2}$, and $B\log X4_{t-1} = \log X4_{t-1} - \log X4_{t-2}$.

In another form, the BVAR(1) model can be represented in each variable as follows:

(1) BVAR equation for Gross Domestic Product, GDP ($X1_t$).

$$\log X1_t = 0.082 + \log X1_{t-1} - 0.003X2_{t-1} + 0.001X3_{t-1} + e_{1t} \tag{15}$$

Equation (15) shows that every 1-unit increase in the logarithm of GDP, 1-unit of renewable energy consumption, and 1-unit of forest area in the previous period's data, will result in an increase of 1 billion in the logarithm of GDP, a decrease of 0.003 billion in the logarithm of GDP, and an increase of 0.001 billion in the logarithm of GDP, respectively. Constantly, there would be 0.082 billion due to the lack of effect from the logarithm of GDP, renewable energy consumption, and forest area in the previous period on the logarithm of GDP in the current period. By transforming GDP $X1_t$ using an exponential function, the BVAR(1) model for GDP $X1_t$ can be represented as follows:

$$X1_t = 1.085X1_{t-1}\frac{\exp(0.001\,X3_{t-1})}{\exp(0.003\,X2_{t-1})}+e_{1t} \tag{16}$$

(2) BVAR equation for Renewable Energy Consumption ($X2_t$).

$$X2_t = -1.165 + X2_{t-1} - 0.002X3_{t-1} + e_{2t} \tag{17}$$

Equation (17) shows that every increase of 1 unit of renewable energy and 1 unit of forest area in the previous period will increase 1 billion GDP and decrease by 0.002 billion GDP or 2 million GDP, respectively. There is a decrease of 1.165 billion in GDP when there is no effect from GDP, renewable energy, forest area, and carbon dioxide.

(3) BVAR Equation for Forest Area ($X3_t$)

$$X3_t = -0.428 + 0.001X2_{t-1} + 0.998X3_{t-1} + e_{3t} \tag{18}$$

Equation (18) shows that every 1-unit increase in renewable energy consumption and 1-unit forest area in the previous period will increase 0.001 and 0.998 billion GDP, respectively. Constantly, there is a decrease of 0.428 billion GDP when there is no effect from GDP, renewable energy consumption, forest area, and carbon dioxide.

(4) BVAR Equation for Carbon Dioxide Emissions ($X4_t$)

$$\log X4_t = 0.035 - 0.001X2_{t-1} + 0.001X3_{t-1} + \log X4_{t-1} + e_{4t} \tag{19}$$

Equation (19) shows that every 1-unit increase in renewable energy, 1-unit forest area, and 1-unit logarithm of carbon dioxide emissions in the previous period's data, respectively, will lead to a decrease of 0.001 billion in the logarithm of GDP, an increase of 0.001 billion in the logarithm of GDP, and a 1 billion logarithm of carbon dioxide emissions. Constantly, there is 0.035 billion when no effect is observed from the logarithm of GDP, renewable energy, forest area, and the logarithm of carbon dioxide emissions in the previous period on the logarithm of GDP in the current period. By transforming carbon dioxide emissions $X4_t$ using an exponential function, the BVAR(1) model for carbon dioxide emissions $X4_t$ can be represented as follows:

$$X4_t = 1.036\,\frac{\exp(0.001\,X3_{t-1}).\exp X4_{t-1}}{\exp(0.001\,X2_{t-1})}+e_{4t} \tag{20}$$

The Σ matrix in Equation (14) provides an overview of the internal variation and relationship between variables in the BVAR model. The variance-covariance matrix of BVAR model refers to a measure of uncertainty or dispersion in the model, showing relationship between the variables being analyzed. In BVAR(1) model, where the order of AR model is 1, the matrix calculates the covariance and variance of the residuals (error terms) among the variables at a given lag based on the posterior distribution.

The elements on the diagonal of the variance-covariance matrix in Equation (14) represent the residual variance of each variable. This shows uncertainty in the prediction, which is referred to as the residual variance of the model. Each off-diagonal element in the variance-covariance matrix measures the degree of relationship between two different variables. A larger value (positive or negative) shows a stronger relationship between the residuals of the two variables, indicating their covariance. The variance-covariance matrix derived from the posterior distribution, incorporates both observed data and priors used in the BVAR estimation. It shows the uncertainty after combining information from the data and priors. Furthermore, the variance-covariance matrix shows how a shock to one variable can affect another in the future through the propagation of dynamics in the VAR model. This variance-covariance matrix is important for understanding relationship between variables in the short run and for sensitivity analysis in BVAR model.

In explaining the residual variance value, there is a variance value in the $\log X1_t$ or the logarithm of GDP is $\Sigma_{11} = 0.035$. In the $X2_t$ variable or renewable energy consumption is $\Sigma_{22} = 1.847$, in the $X3_t$ variable or forest area is $\Sigma_{33} = 0.303$, and in the $\log X4_t$ variable or the logarithm of carbon dioxide emissions is $\Sigma_{44} = 0.004$. Higher variance shows greater fluctuation or uncertainty. Meanwhile, there is a covariance between the GDP variable $(X1_t)$ and renewable energy $(X2_t)$, namely $\Sigma_{12} = \Sigma_{21} = -0.082$. This shows that there is an inverse relationship (negative) between GDP and renewable energy. A covariance between the GDP variable $(X1_t)$ and forest area $(X3_t)$ namely $\Sigma_{13} = \Sigma_{31} = 0.004$, shows a unidirectional (positive). There is a covariance between the variables of GDP $(X1_t)$ and carbon dioxide emissions $(X4_t)$ namely $\Sigma_{14} = \Sigma_{41} = 0.002$, showing a unidirectional (positive). A covariance also exists between the variables of renewable energy consumption $(X2_t)$ and forest area $(X3_t)$, namely $\Sigma_{23} = \Sigma_{32} = 0.066$, showing a unidirectional (positive). There is a covariance between variables of renewable energy consumption $(X2_t)$ and carbon dioxide emissions $(X4_t)$, namely $\Sigma_{24} = \Sigma_{42} = -0.041$, showing an inverse relationship (negative). A covariance exists between the variables of forest area $(X3_t)$ and carbon dioxide emissions $(X4_t)$, namely $\Sigma_{34} = \Sigma_{43} = -0.004$, showing an inverse relationship (negative). This is caused by the increasingly narrow forest area, which increases carbon dioxide emissions due to the reduced absorption carried out by green plants.

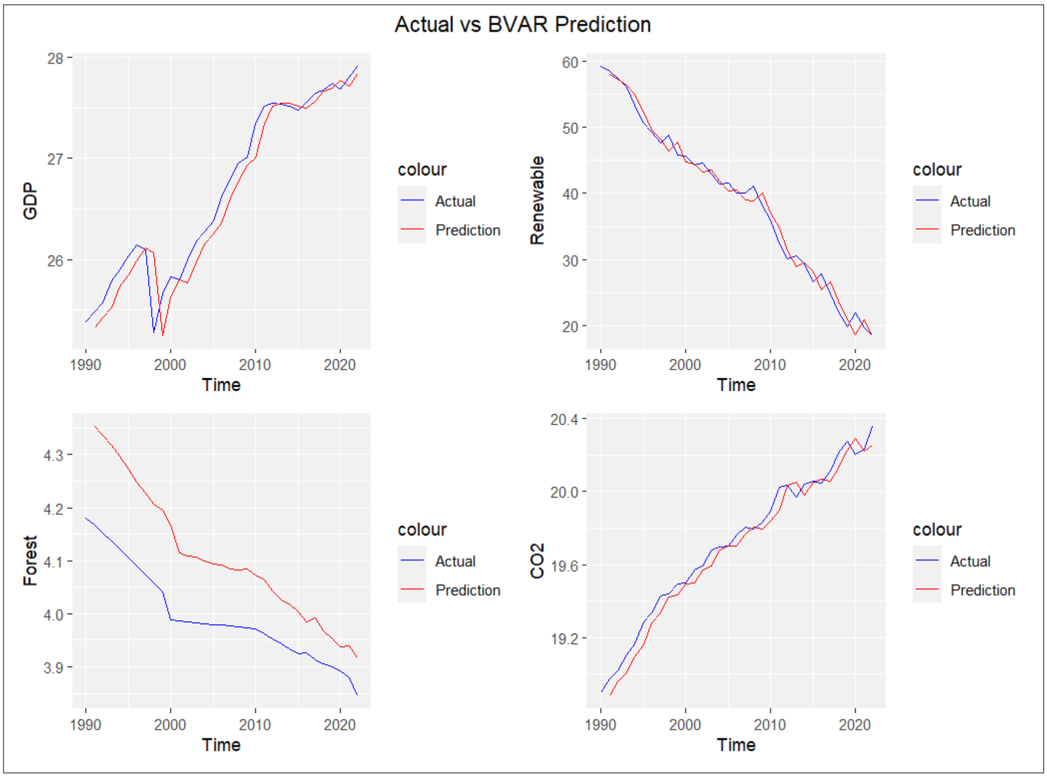

Figure 5. Actual Data vs. BVAR Prediction

After obtaining BVAR(1), the model for each variable and actual data is graphically, as shown in Figure 5. The blue line shows the actual data and the red line represents the data from the previously obtained BVAR(1) model prediction results. The graph also shows that with a small amount of data, the model can still predict the existing data. Subsequently, the residuals of each variable model are obtained, as shown in Figure 6, showing fluctuation around zero. This pattern suggests the residuals are approaching zero, where the assumption that the residuals are spread out as white noise is met. Therefore, the residuals approach zero because the BVAR(1) model is approximately precise and can predict actual data with high performance.

Additionally, the residuals of the BVAR(1) model, depicted in Figure 6, exhibit fluctuations around zero, confirming that the errors are unbiased and meet the assumption of white noise. This pattern suggests that the residuals are random and uncorrelated, with no systematic deviation, which is critical for validating the model's reliability. The residuals' behavior indicates that the model does not systematically overestimate or underestimate the data. The combination of these results demonstrates the robustness of the BVAR(1) model in predicting economic and environmental variables with high precision. The small residuals and the accurate fit between actual and predicted values reinforce the model's utility for analyzing the dynamic relationships between variables and forecasting future trends. This precision and adherence to statistical assumptions underscores the BVAR(1) model's effectiveness in providing valuable insights into the interplay between economic growth, energy use, deforestation, and emissions. Figure 7 shows the forecasted BVAR(1) model.

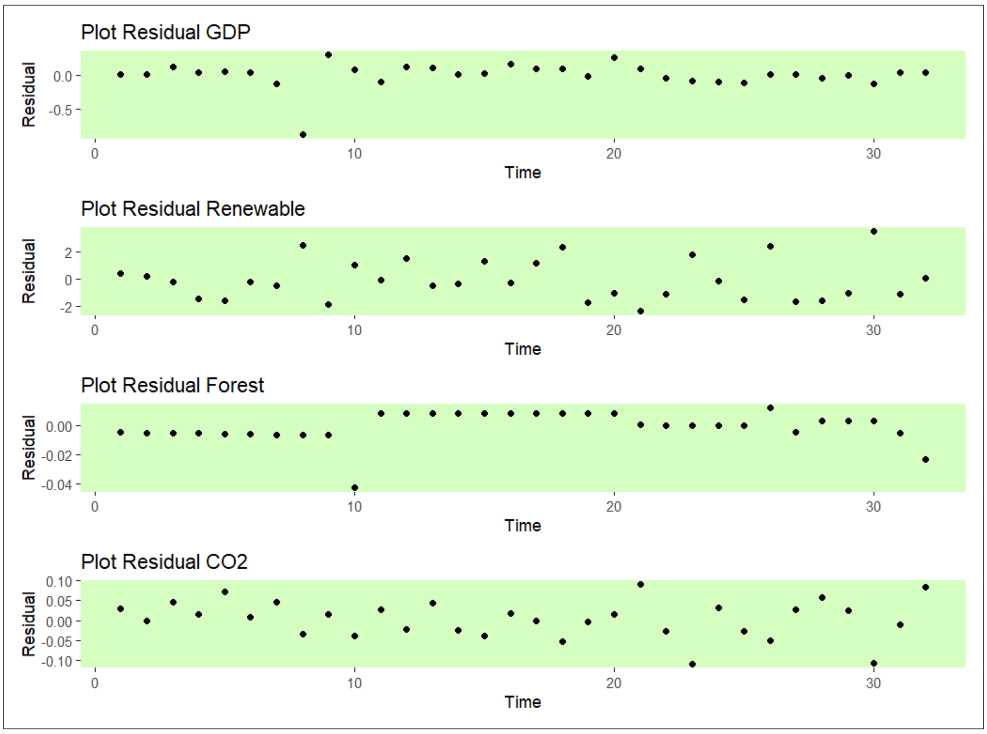

Figure 6. Residual Plot

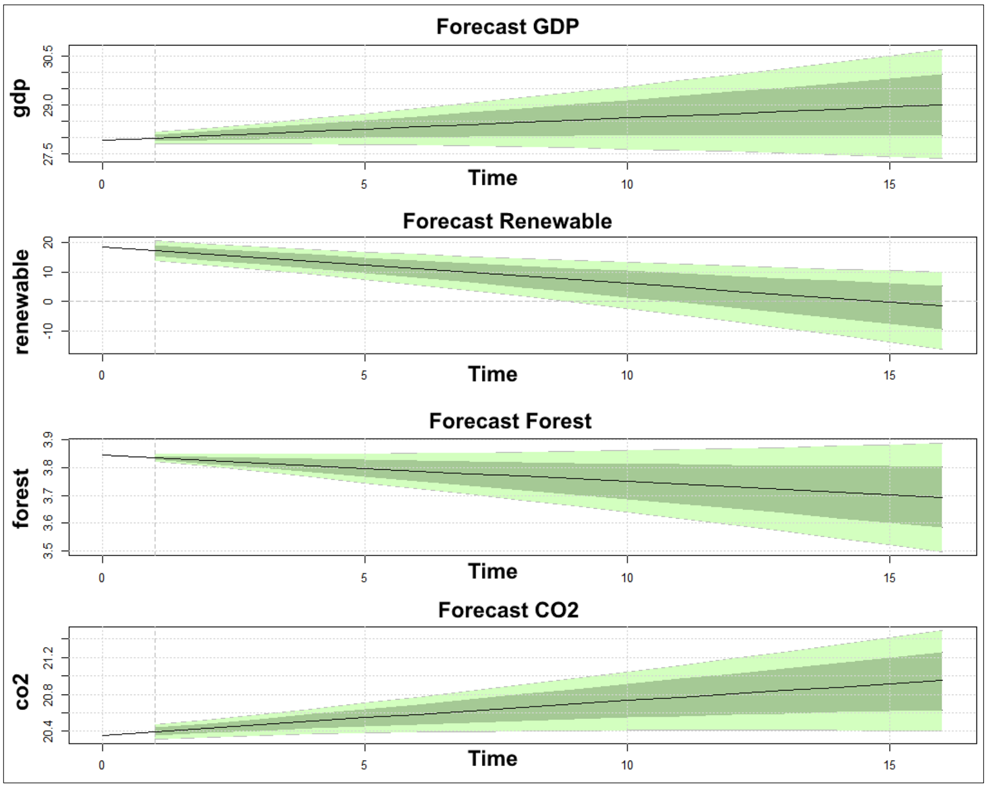

Figure 7. Forecast BVAR

Based on Figure 7, the model predicts that GDP and carbon dioxide emissions increase for the next few years, while forest area and renewable energy consumption will decrease.

This trend highlights the interconnected relationship between the economic growth, environmental degradation, and CO_2 emissions The increasing GDP reflects Indonesia's economic expansion, yet it is accompanied by a decrease in forest area, reducing the country’s ability to absorb CO_2, and a stagnation or even decline in renewable energy consumption. The decline in renewable energy consumption can be attributed to several factors, including inadequate infrastructure, high costs of renewable energy technologies, and continued reliance on fossil fuels. These dynamics exacerbate the challenge of achieving sustainable development, emphasizing the need for more effective policy interventions to promote clean energy and environmental conservation. This finding is also supported by previous research, which underscores the contrasting effects of economic growth (GDP) and renewable energy consumption on CO_2 emissions [37]. While economic growth has been shown to increase emissions, renewable energy consumption plays a critical role in reducing CO_2 emissions. Numerous studies consistently reveal that a shift toward renewable energy sources can help mitigate the environmental impacts of economic expansion. This underscores the importance of integrating renewable energy into economic policies to achieve sustainable growth and reduce carbon footprints. Promoting renewable energy consumption alongside economic growth can serve as a vital strategy in combating climate change and achieving emission reduction targets. Other research also identifies a negative correlation between these variables and CO_2 emissions, suggesting that technological innovation, sustainable agricultural practices, and forest preservation efforts can significantly reduce emissions over time [38]. Policies promoting renewable energy, advancing technological development, supporting climate-conscious agriculture, and ensuring proper forest management must be implemented to achieve environmental sustainability through reduced CO_2 emissions.

One of the primary challenges driving the decline in renewable energy consumption is the limited renewable energy infrastructure. Despite Indonesia's substantial potential in solar, wind, and geothermal energy, the country continues to struggle with developing the infrastructure required to fully integrate these resources into the national grid. According to the International Renewable Energy Agency, Indonesia’s energy grid faces challenges such as insufficient transmission capacity and inadequate energy storage systems, which hinder the widespread adoption of renewable energy. Additionally, high costs of renewable energy technologies, such as solar panels and wind turbines, remain a significant barrier, particularly in rural and underdeveloped areas. This financial challenge is exacerbated by the continued reliance on fossil fuels, which remain artificially cheaper due to government subsidies that lower the cost of coal, oil, and natural gas. These subsidies make fossil fuels more economically attractive than renewable energy sources, which require higher initial investments for technologies such as solar panels, wind turbines, and geothermal systems. As a result, the financial incentive to invest in cleaner energy alternatives is diminished, especially in regions with more pronounced economic constraints. This imbalance discourages private sector investment in renewable energy and delays the necessary infrastructure development for grid integration. Consequently, subsidizing fossil fuels creates a cycle that hinders Indonesia's ability to transition towards a more sustainable and decarbonized energy system, slowing progress in reducing carbon emissions and achieving long-term environmental goals [39].

The continued reliance on fossil fuels remains a significant factor hindering renewable energy growth in Indonesia. Subsidies for fossil fuels make coal and oil cheaper than renewable alternatives, discouraging the transition to cleaner energy sources. Population growth drives higher energy demand, increasing fossil fuel consumption and environmental pollution. Limited investment and slow adoption of renewable energy technologies also contribute to the challenges. Additionally, weak enforcement of environmental regulations allows unsustainable practices, exacerbating the reliance on non-renewable energy [40].

Several factors influence biomass energy development in Indonesia, and the government plays a critical role in addressing these challenges [41]. Policy and regulatory barriers, such as unclear or inconsistent regulations, often complicate project approvals, which can be addressed by strengthening the regulatory framework to streamline processes and ensure environmental compliance. Economic viability is another challenge due to the high upfront costs of biomass projects, requiring the government to expand financial subsidies, tax credits, grants, and low-interest loans to attract investment. Technical and infrastructure limitations also hinder scalability, necessitating government investment in research and development to improve technology efficiency and the development of robust supply chains and distribution networks. Additionally, the lack of awareness and technical expertise among stakeholders, such as farmers and local communities, can be mitigated through capacity-building programs and training initiatives focused on sustainable biomass cultivation and facility operations. Limited collaboration between the private sector, public institutions, and international organizations restricts access to expertise and funding, highlighting the need for government-facilitated partnerships and public-private collaborations. Moreover, sustainability concerns from the overexploitation of biomass resources call for implementing standards that promote responsible utilization and balance environmental, social, and economic impacts. Market demand and pricing uncertainties discourage investment, which can be addressed through attractive feed-in tariffs (FiTs) and secure power purchase agreements (PPAs) to ensure competitive and stable pricing. By addressing these interconnected issues, the government can create a supportive environment for biomass energy development, contributing significantly to the national energy mix while ensuring sustainability and economic growth.

Additionally, stricter environmental regulations and transparent, enforceable policies should be introduced to incentivize the adoption of renewable energy while curbing environmental degradation. Strengthening these measures would enhance investor confidence and ensure that biomass energy projects align with sustainability goals. Furthermore, stronger enforcement of regulations against illegal logging and land burning is crucial to protect Indonesia's forests, which are essential carbon sinks. Illegal logging significantly gives impact to the climate change crisis, as trees are vital for converting CO_2 into oxygen [42]. These efforts are vital in reducing carbon emissions, preserving biodiversity, and maintaining ecological balance. Together, these initiatives can help Indonesia transition to a more sustainable energy future while mitigating the adverse impacts of climate change.

5- Conclusion

In conclusion, this study highlights the issue of CO_2 emissions as a global challenge contributing to environmental degradation phenomenon and climate change. Tackling these emissions necessitates a comprehensive understanding of the key influencing factors, such as economic growth (measured by GDP), renewable energy consumption, and forest area, as illustrated in the case of Indonesia. Despite the limitations posed by data constraints, the BVAR model proved effective in capturing trends and projecting future developments This model predicted that GDP and carbon dioxide emission would increase for the next few years, while forest area and renewable energy consumption decreased significantly. The results showed that the government should implement policy to maintain forest area as well as reduce illegal logging and forest burning in Indonesia. Additionally, there should be continuous advocacy for alternative renewable energy sources, which were proven to be significantly environmentally friendly.

Moreover, the government must prioritize the formulation and implementation of policies that address the underlying drivers of deforestation, including land-use changes spurred by agricultural expansion and urbanization. Strategic interventions are essential to balance economic development with the preservation of critical environmental resources. It could involve promoting sustainable land management practices, enforcing stricter land-use zoning laws, and providing incentives for reforestation and conservation initiatives. Collaboration with local communities is also essential to protect their rights and livelihoods while fostering sustainable use of natural resources. By taking a holistic approach that integrates economic, environmental, and social considerations, Indonesia can create a path toward achieving its climate goals while ensuring the well-being of its citizens and preserving its rich biodiversity. The combination of targeted policy measures, financial incentives, and strong institutional support will be key in transitioning towards a more sustainable, renewable energy-driven future.

The results highlight the urgent need for policy interventions to mitigate the adverse effects of these trends. Specifically, maintaining forest areas through stricter enforcement against illegal logging and forest burning is crucial to preserving Indonesia's natural carbon sinks. Promoting sustainable land-use practices and reforestation initiatives can further support environmental preservation. Simultaneously, accelerating the adoption of renewable energy sources is essential to reduce dependence on fossil fuels and mitigate CO_2 emissions. It requires comprehensive advocacy efforts, increased investment in renewable energy infrastructure, and incentives to encourage its use at both industrial and household levels. Balancing economic growth with environmental sustainability is a challenging yet vital goal, and the insights provided by this research offer a valuable foundation for shaping policies that support both objectives effectively.

6- Declarations

6-1- Author Contributions

Conceptualization, D.D., D.P., and M.Y.; methodology, M.Y., M.M., Y.A., and R.S.; software, M.Y. and R.S.; validation, D.D., M.Y., and R.S.; formal analysis, D.D.; investigation, E.T.H. and M.Y.; resources, R.S. and E.T.H.; data curation, Y.A. and R.S.; writing—original draft preparation, R.S.; writing—review and editing, D.D., M.M., and M.Y.; visualization, R.S. and M.Y.; supervision, D.D. and D.P.; project administration, M.Y.; funding acquisition, D.D. All authors have read and agreed to the published version of the manuscript.

6-2- Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6-3- Funding

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6-4- Institutional Review Board Statement

Not applicable.

6-5- Informed Consent Statement

Not applicable.

6-6- Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the authors.

7- References

[1] Ahmad, K., Irshad Younas, Z., Manzoor, W., & Safdar, N. (2023). Greenhouse gas emissions and corporate social responsibility in USA: A comprehensive study using dynamic panel model. Heliyon, 9(3), 13979. doi:10.1016/j.heliyon.2023.e13979.

[2] Crippa, M., Guizzardi, D., Pagani, F., Banja, M., Muntean, M., Schaaf, E., ... & Vignati, E. (2023). GHG emissions of all world countries. Publications Office of the European Union, Luxembourg City, Luxembourg. doi:10.2760/953322.

[3] Prasetyani, D., Putro, T. R., & Rosalia, A. C. T. (2021). Impact of CO_2 emissions on GDP per capita, FDI, forest area and government spending on education in Indonesia 1991-2020: The GMM methods. IOP Conference Series: Earth and Environmental Science, 905(1), 12131. doi:10.1088/1755-1315/905/1/012131.

[4] Giannelos, S., Bellizio, F., Strbac, G., & Zhang, T. (2024). Machine learning approaches for predictions of CO_2 emissions in the building sector. Electric Power Systems Research, 235, 110735. doi:10.1016/j.epsr.2024.110735.

[5] Li, S., Tong, Z., & Haroon, M. (2024). Estimation of transport CO_2 emissions using machine learning algorithm. Transportation Research Part D: Transport and Environment, 133, 104276. doi:10.1016/j.trd.2024.104276.

[6] Grolleau, G., & Weber, C. (2024). The effect of inflation on CO_2 emissions: An analysis over the period 1970–2020. Ecological Economics, 217, 108029. doi:10.1016/j.ecolecon.2023.108029.

[7] Ganda, F. (2024). The influence of democracy, corruption, economic growth and ICT on carbon emissions in Sub-Saharan African countries: Does FDI matter? Journal of Open Innovation: Technology, Market, and Complexity, 10(3), 100324. doi:10.1016/j.joitmc.2024.100324.

[8] Namahoro, J. P., Wu, Q., Xiao, H., & Zhou, N. (2021). The impact of renewable energy, economic and population growth on CO_2 emissions in the east african region: Evidence from common correlated effect means group and asymmetric analysis. Energies, 14(2), 312. doi:10.3390/en14020312.

[9] Chen, X. H., Tee, K., Elnahass, M., & Ahmed, R. (2023). Assessing the environmental impacts of renewable energy sources: A case study on air pollution and carbon emissions in China. Journal of Environmental Management, 345, 118525. doi:10.1016/j.jenvman.2023.118525.

[10] Xie, H., & Bui, W. K. T. (2024). Impact of globalization and energy consumption on CO_2 emissions in China: Implications for energy transition. Finance Research Letters, 67, 105939. doi:10.1016/j.frl.2024.105939.

[11] Spodniak, P., Ollikka, K., & Honkapuro, S. (2021). The impact of wind power and electricity demand on the relevance of different short-term electricity markets: The Nordic case. Applied Energy, 283, 116063. doi:10.1016/j.apenergy.2020.116063.

[12] Yu, T., Yong, H., & Liu, L. (2023). MCMC-PINNs: A modified Markov chain Monte-Carlo method for sampling collocation points of PINNs adaptively. Authorea Preprints. doi:10.36227/techrxiv.21971678.v1.

[13] Bianco, V., Cascetta, F., & Nardini, S. (2024). Analysis of the carbon emissions trend in European Union. A decomposition and decoupling approach. Science of the Total Environment, 909, 168528. doi:10.1016/j.scitotenv.2023.168528.

[14] Nihayah, D. M., Mafruhah, I., Hakim, L., & Suryanto, S. (2022). CO_2 Emissions in Indonesia: The Role of Urbanization and Economic Activities towards Net Zero Carbon. Economies, 10(4), 72. doi:10.3390/economies10040072.

[15] Raihan, A., Pavel, M. I., Muhtasim, D. A., Farhana, S., Faruk, O., & Paul, A. (2023). The role of renewable energy use, technological innovation, and forest cover toward green development: Evidence from Indonesia. Innovation and Green Development, 2(1), 100035. doi:10.1016/j.igd.2023.100035.

[16] Faruque, M. O., Rabby, M. A. J., Hossain, M. A., Islam, M. R., Rashid, M. M. U., & Muyeen, S. M. (2022). A comparative analysis to forecast carbon dioxide emissions. Energy Reports, 8, 8046–8060. doi:10.1016/j.egyr.2022.06.025.

[17] Raihan, A. (2024). The interrelationship amid carbon emissions, tourism, economy, and energy use in Brazil. Carbon Research, 3(1), 11. doi:10.1007/s44246-023-00084-y.

[18] Ali, A., Audi, M., Senturk, I., & Roussel, Y. (2022). Do Sectoral Growth Promote CO_2 Emissions in Pakistan? Time Series Analysis in Presence of Structural Break. International Journal of Energy Economics and Policy, 12(2), 410–425. doi:10.32479/ijeep.12738.

[19] Adebayo, T. S., Awosusi, A. A., Kirikkaleli, D., Akinsola, G. D., & Mwamba, M. N. (2021). Can CO_2 emissions and energy consumption determine the economic performance of South Korea? A time series analysis. Environmental Science and Pollution Research, 28(29), 38969–38984. doi:10.1007/s11356-021-13498-1.

[20] Koppel, S., Capellan, J. A., & Sharp, J. (2023). Disentangling the Impact of Covid-19: An Interrupted Time Series Analysis of Crime in New York City. American Journal of Criminal Justice, 48(2), 368–394. doi:10.1007/s12103-021-09666-1.

[21] Prinzi, F., Orlando, A., Gaglio, S., & Vitabile, S. (2024). Breast cancer classification through multivariate radiomic time series analysis in DCE-MRI sequences. Expert Systems with Applications, 249, 123557. doi:10.1016/j.eswa.2024.123557.

[22] Rodhan, M. A. (2024). Macroeconomic Impacts of Oil Price Shocks: Evidence from Iraq by Using Vector Autoregressive Model. International Journal of Energy Economics and Policy, 14(3), 162–170. doi:10.32479/ijeep.15681.

[23] Yollanda, M., Harjupa, W., Devianto, D., Andarini, D. F., Nauval, F., Saufina, E., Purwaningsih, A., Harjupa, W., Trismidianto, Harjana, T., Risyanto, Rahmatia, F., Pratama, R., & Satiadi, D. (2023). Prediction of CENS, MJO, and Extreme Rainfall Events in Indonesia Using the VECM Model. Proceedings of the International Conference on Radioscience, Equatorial Atmospheric Science and Environment and Humanosphere Science, INCREASE 2022, Springer Proceedings in Physics, 290, Springer, Singapore. doi:10.1007/978-981-19-9768-6_35.

[24] Devianto, D., Yollanda, M., Maryati, S., Maiyastri, Asdi, Y., & Wahyuni, E. (2023). The Bayesian vector autoregressive model as an analysis of the government expenditure shocks while the covid-19 pandemic to macroeconomic factors. Journal of Open Innovation: Technology, Market, and Complexity, 9(4), 100156. doi:10.1016/j.joitmc.2023.100156.

[25] Sznajderska, A., & Haug, A. A. (2023). Bayesian VARs of the U.S. economy before and during the pandemic. Eurasian Economic Review, 13(2), 211–236. doi:10.1007/s40822-023-00229-9.

[26] Zhang, S., Ma, X., & Cui, Q. (2021). Assessing the Impact of the Digital Economy on Green Total Factor Energy Efficiency in the Post-COVID-19 Era. Frontiers in Energy Research, 9, 798922. doi:10.3389/fenrg.2021.798922.

[27] Andres-Escayola, E., Berganza, J. C., Campos, R. G., & Molina, L. (2023). A BVAR toolkit to assess macrofinancial risks in Brazil and Mexico. Latin American Journal of Central Banking, 4(1), 100079. doi:10.1016/j.latcb.2022.100079.

[28] Hannaford, N. E., Heaps, S. E., Nye, T. M. W., Curtis, T. P., Allen, B., Golightly, A., & Wilkinson, D. J. (2023). A sparse Bayesian hierarchical vector autoregressive model for microbial dynamics in a wastewater treatment plant. Computational Statistics and Data Analysis, 179, 107659. doi:10.1016/j.csda.2022.107659.

[29] Valencia, F. (2024). Time-Series Modelling and Granger Causality Analysis of GDP and Energy Consumption: The Case of Ecuador 1965–2022. Engineering Proceedings, 77(1). doi:10.3390/engproc2024077006.

[30] Yin, C., Wang, C., Wang, Q., & Ge, Y. en. (2024). Effects of regional freight structure and energy intensity on CO_2 emission of transport—a case study in Yangtze River Delta. International Journal of Sustainable Transportation, 18(5), 379–392. doi:10.1080/15568318.2023.2299918.

[31] Cimadomo, J., Giannone, D., Lenza, M., Monti, F., & Sokol, A. (2022). Nowcasting with large Bayesian vector autoregressions. Journal of Econometrics, 231(2), 500–519. doi:10.1016/j.jeconom.2021.04.012.

[32] Doojav, G. O., Purevdorj, M., & Batjargal, A. (2024). The macroeconomic effects of exchange rate movements in a commodity-exporting developing economy. International Economics, 177, 100475. doi:10.1016/j.inteco.2023.100475.

[33] Chan, J. C. C. (2021). Minnesota-type adaptive hierarchical priors for large Bayesian VARs. International Journal of Forecasting, 37(3), 1212–1226. doi:10.1016/j.ijforecast.2021.01.002.

[34] Ameur, H., Njah, H., & Jamoussi, S. (2023). Merits of Bayesian networks in overcoming small data challenges: a meta-model for handling missing data. International Journal of Machine Learning and Cybernetics, 14(1), 229–251. doi:10.1007/s13042-022-01577-9.

[35] Kuschnig, N., & Vashold, L. (2021). BVAR: Bayesian Vector Autoregressions with Hierarchical Prior Selection in R. Journal of Statistical Software, 100(14). doi:10.18637/JSS.V100.I14.

[36] Rudakouski, Y. (2023). Comparing Forecasting Accuracy between BVAR and VAR Models for the Russian Economy. HSE Economic Journal, 27(4), 506–526. doi:10.17323/1813-8691-2023-27-4-506-526.

[37] Kinyar, A., & Bothongo, K. (2024). The impact of renewable energy, eco-innovation, and GDP growth on CO_2 emissions: Pathways to the UK's net zero target. Journal of Environmental Management, 368, 122226. doi:10.1016/j.jenvman.2024.122226.

[38] Raihan, A., Hasan, M. A., Voumik, L. C., Pattak, D. C., Akter, S., & Ridwan, M. (2024). Sustainability in Vietnam: Examining economic growth, energy, innovation, agriculture, and forests' impact on CO_2 emissions. World Development Sustainability, 4, 100164. doi:10.1016/j.wds.2024.100164.

[39] Al-Shetwi, A. Q. (2022). Sustainable development of renewable energy integrated power sector: Trends, environmental impacts, and recent challenges. Science of the Total Environment, 822, 153645. doi:10.1016/j.scitotenv.2022.153645.

[40] Xuan, V. N. (2024). Determinants of environmental pollution: Evidence from Indonesia. Journal of Open Innovation: Technology, Market, and Complexity, 10(4), 100386. doi:10.1016/j.joitmc.2024.100386.

[41] Erdiwansyah, Gani, A., Mamat, R., Bahagia, Nizar, M., Yana, S., Mat Yasin, M. H., Muhibbuddin, & Rosdi, S. M. (2024). Prospects for renewable energy sources from biomass waste in Indonesia. Case Studies in Chemical and Environmental Engineering, 10, 100880. doi:10.1016/j.cscee.2024.100880.

[42] Adeline-Cristina, C., Monica Violeta, A., Codruta, M., & Monica Maria, C. (2025). The moderating role of tourism in the impact of financial crime on deforestation. Journal of Cleaner Production, 486, 144475. doi:10.1016/j.jclepro.2024.144475.