Original Article

Check for updates

Available online at
www.heca-analitika.com/eje

Ekonomikalia
Journal of Economics

Vol. 1, No. 1, 2023

Unveiling the Carbon Footprint: Biomass vs. Geothermal Energy in Indonesia

Ghalieb Mutig Idroes [1], Sofyan Syahnur [2], M. Shabri Abd. Majid [2], Rinaldi Idroes [3], Fitranto Kusumo [4] and Irsan Hardi [1,*]

[1] Economic Modeling and Data Analytics Unit, Graha Primera Saintifika, Aceh Besar 23371, Indonesia; ghaliebidroes@gmail.com (G.M.I.); irsan.hardi@gmail.com (I.H.)
[2] Department of Economics, Faculty of Economics and Business, Universitas Syiah Kuala, Banda Aceh 23111, Indonesia; kabari_sofyan@usk.ac.id (S.S.); mshabri@usk.ac.id (M.S.A.M.)
[3] Department of Chemistry, Faculty of Mathematics and Natural Sciences, Universitas Syiah Kuala, Banda Aceh 23111, Indonesia; rinaldi.idroes@usk.ac.id (R.I.)
[4] Centre for Technology in Water and Wastewater, Faculty of Engineering and Information Technology, University of Technology Sydney, Ultimo 2007 NSW Australia; Fitranto.Kusumo@student.uts.edu.au (F.K.)

* Correspondence: irsan.hardi@gmail.com

Article History

Received 26 May 2023
Revised 18 June 2023
Accepted 29 June 2023
Available Online 5 July 2023

Keywords:
CO_2 emissions
Biomass energy
Geothermal energy
FMOLS
DOLS
ARDL
Granger causality

Abstract

Global climate change, caused by greenhouse gases (GHGs) emissions, particularly carbon dioxide (CO_2), has an enormous and unprecedented impact on our planet's ecosystem, development, and long-run sustainability. This study investigates the dynamic impact of biomass and geothermal energy on CO_2 emissions in Indonesia from 2000 to 2020. Employing the Green Solow model with the approach of Fully-Modified Ordinary Least Squares (FMOLS), Dynamic Ordinary Least Squares (DOLS), Autoregressive Distributed Lag (ARDL) and Pairwise Granger causality test. The cointegration tests suggest the existence of a long-run equilibrium relationship between CO_2 emissions, biomass, and geothermal energy. Empirical evidence reveals that although biomass and geothermal energy positively influence CO_2 emissions, their overall impact is relatively low. This highlights the potential for these renewable energy sources to contribute to CO_2 reduction and promote environmental sustainability. The Granger causality test confirms a causal relationship between CO_2 emissions, biomass, and geothermal energy. Important policy recommendations for promoting sustainable energy practices in Indonesia involve investing in high-quality biomass and geothermal facilities to reduce emissions, implementing energy efficiency programs and fossil fuel conservation measures, and encouraging the use of electricity-based biomass and geothermal energy sources to reduce dependence on non-renewable fuels. These recommendations play a crucial role in achieving environmental and economic sustainability.

1. Introduction

Renewable energy has become the direction of the world's energy focus in providing for domestic energy needs. The significance of renewable energy sources for economic growth and reducing carbon emissions cannot be overstated. As the global community grapples with the challenges posed by climate change and the need for sustainable development, transitioning toward renewable energy has emerged as a key solution [1]. Renewable energy technologies, such as biomass and geothermal power, offer multiple benefits, ranging from environmental preservation to economic prosperity [2].

Indonesia has abundant renewable energy resources such as geothermal, hydropower, biomass, wind, and solar [3, 4]. However, technical and economic limitations make it unlikely for renewables to fully replace fossil fuels in the country's energy mix in the near future. According to Indonesia's National Energy Plan, the government estimates that the country's potential capacity for renewable energy could reach 418 gigawatts, with targets to increase the renewable energy share by 23% in 2025 and 31% in 2050 [5]. The majority of Indonesia's electricity is generated from coal (59.9%), gas (22.3%), and oil (6%), while the remaining 11.8% comes from renewable sources [6]. As people become more conscious of the negative impact of fossil fuels on CO_2 emissions, they are looking for alternate energy sources. Geothermal and biomass energy are sustainable, environmentally friendly alternatives to fossil fuels, with geothermal harnessing the Earth's natural heat and biomass derived from organic materials, both offering reliable power generation with minimal greenhouse gas emissions.

Despite the numerous advantages of biomass and geothermal energy, there are limitations to consider, including the significant costs associated with operating power plants utilizing these energy sources, which encompass expenses for infrastructure, machinery, and workforce. Additionally, using biomass resources can lead to deforestation and a decline in biodiversity due to the requirement for forest clearance. Biomass energy sources cannot match the energy production levels of non-renewable alternatives [7–10]. On the other hand, geothermal systems may pose challenges for homeowners in densely populated urban areas. Geothermal power plants are currently unable to compete with fossil power plants due to the prevailing fuel prices [11]. However, future predictions suggest that investment costs, as well as operational and maintenance expenses, will decrease over time [12]. This cost reduction is expected to be achieved through technological advancements and improvements in production techniques.

Prior Research on Biomass and Geothermal Energy, In G-20 countries, bidirectional causality has been observed between biomass energy consumption and CO_2 emissions, with increased biomass energy consumption leading to reduced CO_2 emissions [13]. In a study encompassing 80 developed and developing countries, it was found that a 100% increase in biomass energy intensity can result in CO_2 emissions ranging from 4% to 47%, whereas a similar increase in fossil fuel consumption can lead to higher CO_2 emissions ranging from 35% to 55% [14]. Additionally, a global review of direct geothermal energy utilization revealed a 40% increase in its application from 2010 to 2015, resulting in energy savings equivalent to 352 million barrels of oil per year and the prevention of 149 million tons of CO_2 emissions [15]. Currently, 26 countries use geothermal resources for electricity generation. Indicates that the development of geothermal resources has a significant potential for reducing CO_2 emissions, with projections suggesting the prevention of approximately 195 million tonnes of CO_2 emissions by 2030 [16]. Utilizing the geothermal potential prevented the release of 48 million tons/year of CO_2 emissions in Turkey [17].

Our study contributes to the existing literature by providing a novel analysis of the dynamic relationship between biomass, geothermal energy and CO_2 emissions in Indonesia, which has not been previously investigated. There are only descriptive studies such as the assessment of biomass open-burning emissions in Indonesia [18], environmental emissions analysis in Indonesian electricity expansion planning with geothermal energy utilization scenarios [19], assessing the potential of CO_2 emission reductions by carbonizing biomass waste from industrial tree plantation in Indonesia [20], an emissions calculation for Indonesia's geothermal power plant [21], and predictability of carbon emissions from biomass burning in Indonesia [22].

This paper seeks to fill the identified gaps by examining the impact of biomass and geothermal energy on CO_2 emissions in both the short and long run, as well as comparing their contributions to environmental quality. The research utilizes econometric techniques, including Fully Modified Ordinary Least Squares (FMOLS), Dynamic Ordinary Least Squares (DOLS), Autoregressive Distributed Lag (ARDL), and Pairwise Granger causality methods. The findings of this study will provide valuable insights for policymakers, enabling them to assess the level of CO_2 emissions generated by biomass and geothermal energy. The results highlight the importance of further investment in renewable energy sources that promote a greener environment.

2. Materials and Methods

2.1. Data Sources and Types

This study uses annual data time series from 2000 to 2020, which are generated from World Development Indicators (WDI) and International Renewable Energy Agency (IREA) database will be used in the study. Further

Table 1. Description of variables.

Variables	Description	Logarithmic forms	Units/Sources	Variable's justification
CO_2	CO_2 emissions	lnCO2	Kilotons (kt)/WDI	Considered an indicator of environmental degradation
GDP	Economic Growth	lnGDP	Per capita (current US$)/WDI	Gross domestic product divided by midyear population
K	Gross Fixed Capital Formation	lnK	(constant 2015 US$)/WDI	Total investment in fixed assets during a specific period, represents the expenditure on acquiring or producing durable goods for production or service provision.
L	Labor Force	lnL	Total (person)/WDI	Total number of employed and unemployed individuals in a specific population or area
GEO	Geothermal Energy	lnGEO	Electricity generation (GWh)/IREA	A class of renewable energy derived from living materials
BIO	Biomass Energy	lnBIO	Electricity generation (GWh)/IREA	A type of renewable energy taken from the Earth's core

details regarding the data and variables utilized in this study can be found in Table 1.

2.2. Fully-Modified Ordinary Least Squares (FMOLS), Dynamic Ordinary Least Squares (DOLS), and Autoregressive Distributed Lag (ARDL)

By extending Solow's classic economic growth model to include environmental considerations, known as the green Solow model [23], the assumption is made that each production process generates negative externalities in the form of environmental degradation. Thus, to enhance environmental conditions, a trade-off must be made by sacrificing some output. In addition, the green Solow model employs a Cobb-Douglas production function model that allows for capital (K) and labor (L) substitution. In this study, we add a variable (R) as a resource so that it appears explicitly in an equation such as Q = f (K, L, R) or $CO_2 = K^{\alpha} L^{\beta} R^{\gamma}$. CO_2 represents environmental degradation, while K, L, and R represent the quantity of capital, labor, and natural resources, respectively. Furthermore, α, β, and γ represent the coefficients of the independent variables K, L, and R, respectively. The Green Solow model was then transformed into Equation 1.

$$CO2_t = f(GDP_t, K_t, L_t, BIO_t, GEO_t) \tag{1}$$

The FMOLS and DOLS methodologies are employed to assess and measure the long-run relationship between the variables. By addressing endogeneity and eliminating serial correlation, these techniques provide more reliable estimates compared to the standard ordinary least squares (OLS) method, particularly when dealing with cointegrated time series data. The econometric model representing the relationship is given in Equation 2 and 3.

$$lnCO2_t = \beta_0 + \beta_1 lnGDP_t + \beta_2 lnK_t + \beta_3 lnL_t + \beta_4 LnBIO_t + \varepsilon_t \tag{2}$$

$$lnCO2_t = \beta_0 + \beta_1 lnGDP_t + \beta_2 lnK_t + \beta_3 lnL_t + \beta_4 LnGEO_t + \varepsilon_t \tag{3}$$

where β_0 is an intercept, ε represents the error term, and β_1, β_2, β_3, and β_4 are the model coefficients.

Furthermore, the ARDL model can distinguish short and long-run responses from the variables to be studied. This CO_2 emissions models are classified to achieve a comprehensive-comparative analysis of CO_2 emissions written in Equation 1. In general, the CO_2 emissions equations models applied in the ARDL model based on [24] represented as Equation 4.

$$\Delta lnCO2_t = \alpha_0 + \sum_{i=1}^{p} \beta_1 \Delta lnCO2_{t-i} + \sum_{i=0}^{p} \beta_2 \Delta lnGDP_{t-i} + \sum_{i=0}^{p} \beta_3 \Delta lnK_{t-i} + \sum_{i=0}^{p} \beta_4 \Delta lnL_{t-i} + \sum_{i=0}^{p} \beta_5 \Delta lnGEO_{t-i} + \sum_{i=0}^{p} \beta_6 \Delta lnBIO_{t-i} + \delta_1 lnCO2_{t-1} + \delta_2 lnGDP_{t-1} + \delta_3 lnK_{t-1} + \delta_4 lnL_{t-1} + \delta_5 lnGEO_{t-1} + \delta_6 lnBIO_{t-1} + \varepsilon_t \tag{4}$$

Where Δ and ε_t refer to the first difference and the error term, *i* and *t* refer to country and time period. The value "ρ" represents the maximum lag-length determined by the Akaike Information Criterion (AIC). In Equation 4, CO_2 is considered the dependent variable expressed in tons, which is a standard international measure; CO_2 represents the number of pollutants produced, as it is regarded as the primary contributor to global warming and environmental degradation. Therefore, it is of the utmost importance to assess the environmental impact of the rise in GDP, K, L, GEO and BIO.

2.3. Granger Causality

In a time series analysis, the Granger causality test demonstrates the causal relationship between each independent and dependent variable. It is a statistical hypothesis test to determine whether 1-time series can

Table 2. Descriptive statistics.

Variable	Obs	Mean	Max	Min	SD
lnCO2	21	12.94	13.33	12.54	0.22
lnGDP	21	7.69	8.33	6.60	0.60
lnK	21	26.01	26.57	25.35	0.40
lnL	21	18.57	18.72	18.42	0.10
lnGEO	21	9.07	9.65	8.57	0.31
lnBIO	21	8.89	9.38	8.36	0.35

Table 3. Unit root test.

Variable	Augmented Dickey-Fuller (ADF)	
	Level (I(0))	1st Difference (I(1))
lnCO2	0.025**	0.009*
lnGDP	0.987	0.018**
lnK	0.999	0.043**
lnL	0.257	0.020**
lnGEO	0.089***	0.024**
lnBIO	0.287	0.003*

Note: I(0)" and "I(1)" stand for the order of integration at level and on the first difference, respectively. *,**,*** represents 1%, 5% and 10% level of significance

predict another. Both the null hypothesis and the alternative hypothesis are employed.

The null hypothesis asserts that the variable does not cause the other variable to Granger, whereas the alternative hypothesis states that the variable does cause the other variable to Granger. The probability value is used to establish if one variable causes the other. If the probability value against the other is 0.05 at a 5% significance threshold, we reject the null hypothesis and adopt the alternative hypothesis that the variable causes the other. There is bidirectional causation if both variables Granger cause one another. This test is included in the study to evaluate the relationship between the variables of interest.

3. Results and Discussion

Before conducting the objective evaluation, the dataset's descriptive nature, including the employed data's normality, must be revealed.

Table 2 Descriptive statistics are used to describe the data in a way that is easier to comprehend, as well as to provide an overview of the study's variables during the 2000-2020 research period. Data used in this study is in the form of a natural logarithm with a standard deviation (SD) value close to 0 indicating that the mean or average of the data set is identical to the dataset. Then there is less data variability, making the average value more reliable.

Before adopting the cointegration test, unit root tests should be conducted to ascertain the nature of the stationarity of the parameters, followed by descriptive statistical tests to determine normality. This stage has significance because it not only assists in determining the type of stationarity of the employed parameter but also in selecting an appropriate test for future research. This investigation employed Augmented Dickey-Fuller (ADF) unit root testing methods. According to Table 3, all investigated parameters are stationary at the first difference. This means there is no possibility of a false regression analysis, as all variables in empirical studies gravitate toward their actual values.

CO_2 emissions and Geothermal energy are shown to be stationary at the level (I(0)) in Table 3, whereas Economic Growth, Capital, Labor and Biomass Energy are not stationary. Consequently, it is necessary to evaluate stationarity at the first difference (I(1)), which demonstrates that the four variables are stationary. In general, the results of the stationary test illustrate the various levels of stationarity of the observed primary variables I(0) and I(1). This distinctive stationary state is presumed to lead to cointegration or a long-run relationship among all the observed primary variables [24, 25].

The next phase of this investigation is to determine the optimal lag for each analyzed primary variable. The optimal lag test explains the amount of lag of each observed variable that has a statistically significant effect or response on the dependent variable. The lag length indicates how long a variable takes to respond to changes in other variables. It is crucial to select the optimal lag when constructing Gaussian residuals, regardless of whether the residuals are free from autocorrelation or heteroscedasticity problems.

To determine the maximum lag of each variable observed in this study, the Akaike Information Criteria (AIC), Schwarz Information Criterion (SIC), Likelihood Ratio Test (LR), Final Prediction Error (FPE), and Hannan-Quinn (HQ) tests are utilized, with the highest number of stars determining the test outcomes. Each lag length test criterion recommends a course of action. LR, FPE, AIC, SIC, and HQ all recommend lag1 based on Table 4 for the CO_2 Emissions model.

Cointegration testing in this study is needed to determine whether the dependent and all independent variables have a long-run equilibrium to examine ARDL. This study employs the Bounds test approach to determine the cointegration condition by comparing the F-statistic and Bounds test critical values. This model will exhibit cointegration if the F-statistic exceeds the upper bound I(1) value. Nonetheless, if the F-statistic is less than the 10% lower bound value I(0), it can be concluded that there is no cointegration condition.

Table 4. Lag optimum test.

Lag	LogL	LR	FPE	AIC	SIC	HQ
0	156.5871	NA	1.16e-14	-15.05871	-14.75999	-15.00040
1	262.0221	137.0654*	1.35e-17*	-22.00221*	-19.91117*	-21.59401*

Table 5. Cointegration of Bound-test.

		1% critical values		5% critical values		10% critical values	
Model	**F-statistics**	**I(0)**	**I(1)**	**I(0)**	**I(1)**	**I(0)**	**I(1)**
$\mathbf{CO2_t = f(GDP_t, K_t, L_t, GEO_t, BIO_t)}$	6.834698	2.82	4.21	2.14	3.34	1.81	2.93

Table 6. Results of FMOLS and DOLS estimation.

Variable	$\mathbf{CO2_t = f(GDP_t, K_t, L_t, BIO_t)}$		$\mathbf{CO2_t = f(GDP_t, K_t, L_t, GEO_t)}$	
	FMOLS	**DOLS**	**FMOLS**	**DOLS**
lnGDP	-0.0109 (-0.19)	0.0257 (0.32)	-0.0161 (-0.23)	0.0565 (0.77)
lnK	0.2313 (1.28)	0.2643 (1.04)	0.3101 (1.59)	0.2484 (1.18)
lnL	0.2266 (1.15)	0.2078 (0.75)	0.1237 (0.57)	0.2174 (0.94)
lnBIO	0.3161 (2.61)**	0.2257 (1.33)	-	-
lnGEO	-	-	0.2978 (2.70)**	0.2205 (1.86)***

Note: *, ** and *** denote the statistical significance at the 1%, 5% and 10% levels, respectively.

The results of the Bound test in Table 5 show that the F-Statistic in the CO_2 emissions model is greater than the critical value at the upper Bound at 1% (4.21), 5% (3.34), and 10% (2.93). It can be interpreted that H_0, which states no cointegration between variables, can be rejected, and the alternative hypothesis (H_1) is accepted. It means that there is the existence of a cointegration condition between long-run adjustments. It is concluded that the model has a cointegration between the short and long-run equilibrium.

After investigating the optimal lag and cointegration test, the structural stability test of the parameter on the axis cumulative sum of recursive residuals (CUSUM) and cumulative sum of recursive residuals squares (CUSUMSQ) approaches to evaluate the robustness of models. Recursive residual is the standard residue from a regression group where the number of samples increases from the smallest to the total sample, and stability results are displayed in Figure 1.

Based on the CUSUM and CUSUMQ tests, all quantitative plots Wr do not cross the 5% significance level boundary line (significant line, Sr) where the plot is a linear line in CUSUMQ. This research model is therefore highly applicable for estimating the dynamic impact of geothermal and biomass energy on CO_2 emissions in Indonesia.

3.1. Result of FMOLS and DOLS Estimation

According to Table 6, BIO and GEO have the same significance level at the 5% based on FMOLS results in terms of influencing CO_2 over the long run. However, according to the DOLS results, only GEO significantly affects CO_2. As shown, FMOLS results give empirical evidence that GEO has a smaller positive coefficient than BIO, meaning increasing CO_2 by 0.29% for every 1% rise in GEO is lower than increasing CO_2 by 0.31% for every 1% increase in BIO. Based on the results of these two methods, it concluded that GEO produces lower CO_2 emissions than BIO in the long run.

3.2. Result of ARDL Estimation

The objective of ARDL is to examine the dynamic impact of BIO and GEO energy on CO_2. Furthermore, Table 7 revealed a relatively high Adjusted R-squared of 98.22%. This suggests that the independent variables explain properly CO_2 levels. As a result, CO_2 is jointly influenced by the chosen independent variables.

Table 7 of the CO_2 emission ARDL model as the dependent variable with the selected Lag (1, 0, 0, 1, 1, 1) reveals a negative effect of BIO and GEO on CO_2. However, both energy variables reduce CO_2 in the short-run, but sadly insignificant, with a p-value of 60% for BIO and 25% for GEO. Greater than the significance levels of 10%.

Furthermore, both in Lag(-1), BIO and GEO significantly positively affect CO_2; 1.0% increase in BIO and GEO increases CO_2 by 0.29% and 0.37% in the short run. According to the short-run estimation results, the coefficient of GEO tends to be greater than that of BIO, indicating that GEO emits more CO_2 into the atmosphere.

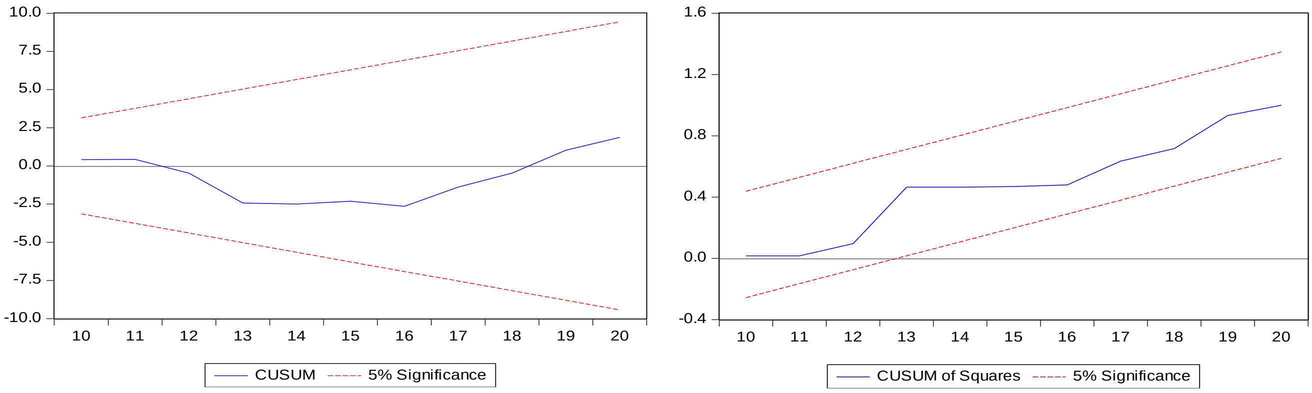

Figure 1. Model stability (CUSUM and CUSUMQ) for CO_2 emissions model.

Table 7. Results of ARDL estimation.

Dependent variable $\mathbf{CO2_t = f(GDP_t, K_t, L_t, GEO_t, BIO_t)}$

Variable	**Coeff.**	**Std. Er.**	**t-Stat.**	**Prob.**
Short-run				
lnCO2(-1)	0.076	0.156	0.490	0.633
lnGDP	-0.032	0.054	-0.601	0.560
lnK	0.095	0.196	0.485	0.636
lnL	2.901*	0.755	3.838	0.002
lnL(-1)	-2.599*	0.730	-3.559	0.004
lnBIO	-0.062	0.119	-0.526	0.608
lnBIO(-1)	0.290**	0.130	2.221	0.048
lnGEO	-0.150	0.125	-1.192	0.258
lnGEO(-1)	0.379**	0.151	2.507	0.029
Long-run				
lnGDP	-0.035	0.059	-0.603	0.558
lnK	0.103	0.208	0.497	0.628
lnL	0.327	0.229	1.427	0.181
lnBIO	0.246	0.151	1.625	0.132
lnGEO	0.248**	0.104	2.383	0.036
R-squared 0.9897				
Adjusted R-squared 0.9822				

Note: *, ** and *** denote the statistical significance at the 1%, 5% and 10% levels, respectively.

A previous study about the impact of geothermal energy on CO_2 emissions in the top seven geothermal energy-consuming nations revealed that geothermal energy reduces CO_2 emissions in Italy, Mexico, and New Zealand at specific quantiles while increasing CO_2 emissions in India, the USA, Turkey, and the Philippines; moreover, geothermal energy serves as a predictor of CO_2 emissions across all nations [26]. Furthermore, the study explores the association between emissions, economic development, and biomass energy using a balanced panel dataset consisting of 38 selected countries from Asia. The results reveal that biomass energy significantly impacts environmental damage [27].

In the long run, BIO does not significantly affect CO_2. However, GEO was found to influence CO_2 significantly; 1.0% increase in geothermal energy will raise CO_2 by 0.24% in the long run. In addition, GEO also provides empirical evidence that, in the long run, it produces lower CO_2 compared to the short run.

A preliminary study on geothermal energy indicates a positive coefficient in the short run, suggesting a counter-intuitive finding that geothermal energy's contribution to reducing carbon emissions becomes evident primarily in the long run [28]. Geothermal power plants produce electricity without burning fuel, resulting in minimal emissions of sulfur dioxide and carbon dioxide. Compared to fossil fuel power plants of similar capacity, geothermal power plants release approximately 97% less sulfur compounds that contribute to acid rain and about 99% less carbon dioxide [29].

Table 8. The Pairwise Granger causality test results.

Null hypothesis	F-statistics	P-Value	Results
GDP ⇏ CO2	2.73014	0.1168	
CO2 ⇏ GDP	0.80483	0.3822	
K ⇏ CO2	7.15367	0.0160**	K → CO2
CO2 ⇏ K	0.04580	0.8331	
L ⇏ CO2	4.22936	0.0554***	L → CO2
CO2 ⇏ L	0.67176	0.4238	
BIO ⇏ CO2	8.65759	0.0091*	BIO → CO2
CO2 ⇏ BIO	1.24334	0.2803	
GEO ⇏ CO2	12.9804	0.0022*	GEO → CO2
CO2 ⇏ GEO	0.29873	0.5918	
K ⇏ GDP	0.20143	0.6592	
GDP ⇏ K	6.34421	0.0221**	GDP → K
L ⇏ GDP	1.40863	0.2516	
GDP ⇏ L	3.89563	0.0649***	GDP → L
BIO ⇏ GDP	2.35625	0.1432	
GDP ⇏ BIO	4.93260	0.0402**	GDP → BIO
GEO ⇏ GDP	0.12165	0.7315	
GDP ⇏ GEO	0.09776	0.7583	
K ⇏ K	0.22788	0.6392	
L ⇏ K	4.20790	0.0560***	L → K
BIO ⇏ K	0.00136	0.9710	
K ⇏ BIO	5.47026	0.0318**	K → BIO
GEO ⇏ K	1.30979	0.2683	
K ⇏ GEO	2.04828	0.1705	
BIO ⇏ L	0.01097	0.9178	
L ⇏ BIO	6.68572	0.0192**	L → BIO
GEO ⇏ L	1.15032	0.2985	
L ⇏ GEO	4.88413	0.0411**	L → GEO
GEO ⇏ BIO	1.83748	0.1930	
BIO ⇏ GEO	1.03733	0.3227	

Note: *, ** and *** denote the statistical significance at the 1%, 5% and 10% levels, respectively.

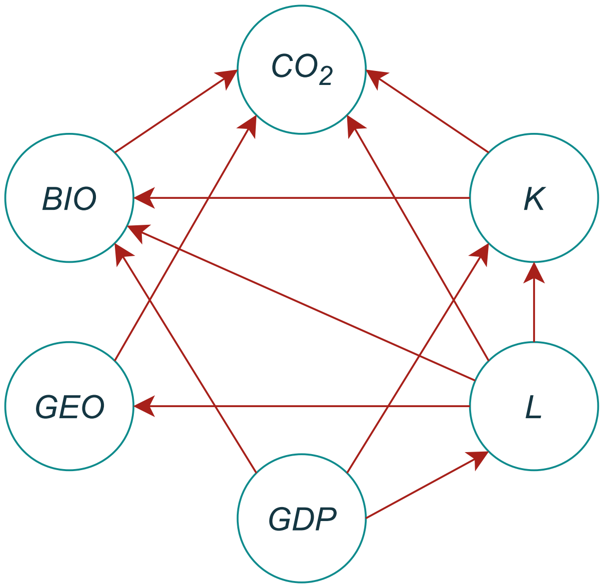

Figure 2. Overview of the results from Pairwise Granger causality analysis.

3.3. Results of Pairwise Granger Causality

The existence of long-run cointegration relationships among variables implies the presence of causality in at least one direction, as stated by [30]. The Pairwise Granger causality test examines the causal relationships between variables in pairs, drawing directly from the Granger causality concept [31, 32]. According to this concept, if a time-series Y can predict the future values of a time-series X, it indicates that Y "Granger-causes" X. Including past observations of Y in the framework is more likely to reduce the prediction error of X compared to using past observations of X alone [33]. The Granger causality tests are conducted simultaneously on all variables within a system of n variables. In this study, the Pairwise Granger Causality test is employed to analyze the entire system. The test employs the Fisher-statistic to test the null hypothesis of no causality between the two variables.

Granger causality demonstrated a one-way relationship between total CO_2 emissions, economic growth, capital, labor, biomass, and geothermal energy. The main findings of this investigation are summarized in Figure 2.

Table 8 shows the paired Granger causality test findings, demonstrating no bidirectional causality between variables. However, unidirectional causality was found from capital, labor, biomass, and geothermal to CO_2 emissions, economic growth and labor to capital, and economic growth, capital, and labor to biomass. The final unidirectional causality is from economic growth to labor, and labor to geothermal.

The Granger causality results indicate a unidirectional causality from biomass and geothermal energy to CO_2 emissions. Similarly, biomass energy consumption shows a unidirectional and immediate causal impact on total CO_2 emissions [34]. In contrast, other findings have reported a bidirectional causality between geothermal energy and CO_2 emissions in the Philippines [28].

4. Conclusions and Recommendations

Undoubtedly, energy is now recognized as a crucial component of production, yet its generation and usage are associated with adverse environmental effects, leading to climate change. As explored in this paper and recent energy literature, the nature and attributes of the generated energy play an even more significant role. Considering the environmental commitments of nations under international climate change agreements, it is crucial, at present, to prioritize environmentally sustainable alternative energy sources over conventional ones. The adoption of these sources is facilitated by technological advancements in the sector and the declining costs of renewable energy installation.

Biomass power facilities not only provide rural communities with opportunities to generate income through biomass cultivation and supply, as well as Indonesia's strategic location within the Pacific Ring of Fire for geothermal energy, but they also provide the potential to reduce reliance on fossil fuels. In Indonesia, biomass and geothermal energy contributes to efforts to reduce carbon emissions and attain environmental sustainability. The government has implemented policies and programs, such as an energy policy focused on supporting the development and dissemination of renewable power generation (feed-in tariffs) and incentives to encourage the development of biomass and geothermal energy and power facilities.

Our findings demonstrate a significant influence of both biomass and geothermal energy on CO_2 emissions, particularly in the long run. Additionally, our empirical evidence suggests that although biomass and geothermal energy positively impact CO_2 emissions, the extent of this impact is relatively low. This highlights the potential of these renewable energy sources to play a role in reducing carbon emissions and promoting environmental sustainability.

In addition to demonstrating the significant impact of biomass and geothermal energy on CO_2 emissions, our study also compares their effectiveness in reducing CO_2 emissions. Our findings indicate that geothermal energy is slightly more effective in reducing CO_2 emissions. Therefore, it is essential to highlight that both biomass and geothermal energy can significantly contribute to CO_2 emission reduction and enhance environmental quality.

Important policy recommendations can be formulated. First, we suggest that the Indonesian government should further invest in technologies to build high-quality facilities for biomass and geothermal energies that could reduce emission rates. Second, as Indonesia is one of the most populous countries characterized by a booming power demand, it is crucial to implement energy efficiency programs, such as biomass and geothermal energy, coupled with careful fossil fuel conservation measures. Third, given the over-dominance of non-renewable fuels in Indonesia's electricity mix (89% in 2015), reconciling the booming power demand from the industry with environmental objectives should involve a significant deployment of electricity-based biomass and geothermal energy inputs. These recommendations would not only reduce the heavy dependence of the power sector on the traditional use of non-renewable energy but also contribute to achieving environmental and economic development sustainability.

However, it should be noted that this study faces significant limitations due to the unavailability of data for certain variables in Indonesia that were included in the analysis. Consequently, this study's timeframe is limited from 2000 to 2020, and the researchers would have preferred to extend it to more recent years, such as 2022.

Author Contributions: Conceptualization, G.M.I., I.H., S.S. and R.I.; methodology, G.M.I., I.H. and M.S.A.M.; software, G.M.I. and I.H.; validation, G.M.I., I.H., F.K., M.S.A.M. and S.S.; formal analysis, G.M.I. and I.H.; investigation, G.M.I. and I.H.; resources, G.M.I., I.H. and R.I.; data curation, G.M.I.; writing—original draft preparation, G.M.I. and I.H.; writing—review and editing, G.M.I., I.H. and F.K.; visualization, G.M.I., I.H. and F.K.; supervision, R.I., M.S.A.M. and S.S.; project administration, G.M.I. and I.H.; All authors have read and agreed to the published version of the manuscript.

Funding: This study does not receive external funding.

Data Availability Statement: The data is available by request.

Acknowledgments: The authors express their gratitude to their institutions and universities.

Conflicts of Interest: All the authors declare that there are no conflicts of interest.

References

1. United Nations. (2023). Renewable energy – powering a safer future
2. Strielkowski, W., Civín, L., Tarkhanova, E., Tvaronavičienė, M., and Petrenko, Y. (2021). Renewable Energy in the Sustainable Development of Electrical Power Sector: A Review, *Energies*, Vol. 14, No. 24, 8240. doi:10.3390/en14248240
3. Bahri, R. A., Noviandy, T. R., Suhendra, R., Idroes, G. M., Yanis, M., Yandri, E., Nizamuddin, N., and Irvanizam, I. (2023). Utilization of Drone with Thermal Camera in Mapping Digital Elevation Model for Ie Seu'um Geothermal Manifestation Exploration Security, *Leuser Journal of Environmental Studies*, Vol. 1, No. 1, 25–33. doi:https://doi.org/10.60084/ljes.v1i1.40
4. Idroes, G. M., Syahnur, S., Majid, S. A., Sasmita, N. R., and Idroes, R. (2021). Provincial economic level analysis in Indonesia based on the geothermal energy potential and growth regional domestic products using cluster analysis, *IOP Conference Series: Materials Science and Engineering*, Vol. 1087, No. 1, 012079. doi:10.1088/1757-899X/1087/1/012079
5. Silalahi, D. F., Gunawan, D., Wahyuni, E., Dipayana, G. F., Hardhi, M., Winofa, N. C., Ramadhan, R. A., and Hidayat, T. (2022). *Indonesia Post-Pandemic Outlook: Strategy towards Net-Zero Emissions by 2060 from the Renewables and Carbon-Neutral Energy Perspectives*, (H. Ardiansyah & P. Ekadewi, Eds.), Penerbit BRIN. doi:10.55981/brin.562
6. Hartono, D., Hastuti, S. H., Halimatussadiah, A., Saraswati, A., Mita, A. F., and Indriani, V. (2020). Comparing the impacts of fossil and renewable energy investments in Indonesia: A simple general equilibrium analysis, *Heliyon*, Vol. 6, No. 6, e04120. doi:10.1016/j.heliyon.2020.e04120
7. Aydin, M. (2019). The effect of biomass energy consumption on economic growth in BRICS countries: A country-specific panel data analysis, *Renewable Energy*, Vol. 138, 620–627. doi:10.1016/j.renene.2019.02.001
8. Tun, Z. M., Christwardana, M., Adiguna, R., Hadiyanto, H., and Windarta, J. (2023). A Mini Review on The Biomass Energy

Implementation from Economic Perspective in Indonesia, *Journal of Bioresources and Environmental Sciences*, Vol. 2, No. 1, 101–108. doi:10.14710/jbes.2023.17067

9. Bilgili, F., Koçak, E., Bulut, Ü., and Kuşkaya, S. (2017). Can biomass energy be an efficient policy tool for sustainable development?, *Renewable and Sustainable Energy Reviews*, Vol. 71, 830–845. doi:10.1016/j.rser.2016.12.109
10. Wang, Z., Bui, Q., and Zhang, B. (2020). The relationship between biomass energy consumption and human development: Empirical evidence from BRICS countries, *Energy*, Vol. 194, 116906. doi:10.1016/j.energy.2020.116906
11. Abed Almoussaw, Z., Abdul Karim, N., Taher Braiber, H., Ali Abd Alhasan, S., Raheem Alasadi, S., H Ali Omran, A., Tariq Kalil, Z., V Pavlova, I., and Alabdallah, Z. (2022). Analysis of geothermal energy as an alternative source for fossil fuel from the economic and environmental point of view: A case study in Iraq, *Caspian Journal of Environmental Sciences*, Vol. 20, No. 5, 1127–1133
12. Al-Kayiem, H., and Mohammad, S. (2019). Potential of Renewable Energy Resources with an Emphasis on Solar Power in Iraq: An Outlook, *Resources*, Vol. 8, No. 1, 42. doi:10.3390/resources8010042
13. DESTEK, M. A., and OKUMUŞ, İ. (2019). Biomass Energy Consumption, Economic Growth and CO2 Emission in G-20 Countries, *Anemon Muş Alparslan Üniversitesi Sosyal Bilimler Dergisi*, Vol. 7, No. 1, 347–353. doi:10.18506/anemon.453801
14. Solarin, S. A., Al-Mulali, U., Gan, G. G. G., and Shahbaz, M. (2018). The impact of biomass energy consumption on pollution: evidence from 80 developed and developing countries, *Environmental Science and Pollution Research*, Vol. 25, No. 23, 22641–22657. doi:10.1007/s11356-018-2392-5
15. Lund, J. W., and Boyd, T. L. (2016). Direct utilization of geothermal energy 2015 worldwide review, *Geothermics*, Vol. 60, 66–93. doi:10.1016/j.geothermics.2015.11.004
16. Yousefi, H., Abbaspour, A., and Seraj, H. (2019). The Role of Geothermal Energy Development on CO 2 Emission by 2030, *Proceedings of the 44th Workshop on Geothermal Reservoir Engineering, Stanford, CA, USA*, 11–13
17. Kömürcü, M. İ., and Akpınar, A. (2009). Importance of geothermal energy and its environmental effects in Turkey, *Renewable Energy*, Vol. 34, No. 6, 1611–1615. doi:10.1016/j.renene.2008.11.012
18. Permadi, D. A., and Kim Oanh, N. T. (2013). Assessment of biomass open burning emissions in Indonesia and potential climate forcing impact, *Atmospheric Environment*, Vol. 78, 250–258. doi:10.1016/j.atmosenv.2012.10.016
19. Tanoto, Y., and Wijaya, M. E. (2011). Economic and environmental emissions analysis in Indonesian electricity expansion planning: Low-rank coal and geothermal energy utilization scenarios, *2011 IEEE Conference on Clean Energy and Technology (CET)*, IEEE, 177–181. doi:10.1109/CET.2011.6041459
20. Okimori, Y., Ogawa, M., and Takahashi, F. (2003). Potential of Co 2 emission reductions by carbonizing biomass waste from industrial tree plantation in South Sumatra, Indonesia, *Mitigation and Adaptation Strategies for Global Change*, Vol. 8, No. 3, 261–280. doi:10.1023/B:MITI.0000005643.79908.5a
21. Yuniarto, T., and Heviati, E. (2015). Geothermal Power Plant Emissions in Indonesia, *Proceedings of the World Geothermal Congress, Melbourne, Australia*, Citeseer, 19–25
22. Field, R. D., and Shen, S. S. P. (2008). Predictability of carbon emissions from biomass burning in Indonesia from 1997 to 2006, *Journal of Geophysical Research: Biogeosciences*, Vol. 113, No. G4. doi:10.1029/2008JG000694
23. Brock, W. A., and Taylor, M. S. (2010). The Green Solow model, *Journal of Economic Growth*, Vol. 15, No. 2, 127–153. doi:10.1007/s10887-010-9051-0
24. Pesaran, M. H., Shin, Y., and Smith, R. J. (2001). Bounds testing approaches to the analysis of level relationships, *Journal of Applied Econometrics*, Vol. 16, No. 3, 289–326. doi:10.1002/jae.616
25. Pesaran, M. H., and Shin, Y. (1995). *An Autoregressive Distributed Lag Modelling Approach to Cointegration Analysis* (Vol. 9514), Department of Applied Economics, University of Cambridge Cambridge, UK
26. Umar, M., Awosusi, A. A., Adegboye, O. R., and Ojekemi, O. S. (2023). Geothermal energy and carbon emissions nexus in leading geothermal-consuming nations: Evidence from nonparametric analysis, *Energy & Environment*, 0958305X2311539. doi:10.1177/0958305X231153972
27. Shah, S. A. R., Naqvi, S. A. A., Riaz, S., Anwar, S., and Abbas, N. (2020). Nexus of biomass energy, key determinants of economic development and environment: A fresh evidence from Asia, *Renewable and Sustainable Energy Reviews*, Vol. 133, 110244. doi:10.1016/j.rser.2020.110244
28. Shahzad, U., Schneider, N., and Ben Jebli, M. (2021). How coal and geothermal energies interact with industrial development and carbon emissions? An autoregressive distributed lags approach to the Philippines, *Resources Policy*, Vol. 74, 102342. doi:10.1016/j.resourpol.2021.102342
29. U.S. Energy Information Administration. (2022). Geothermal explained, Geothermal energy and the environment
30. Granger, C. W. J. (2003). Some aspects of causal relationships, *Journal of Econometrics*, Vol. 112, No. 1, 69
31. Granger, C. W. J. (1969). Investigating Causal Relations by Econometric Models and Cross-spectral Methods, *Econometrica*, Vol. 37, No. 3, 424. doi:10.2307/1912791
32. Granger, C. W. J. (1988). Some recent development in a concept of causality, *Journal of Econometrics*, Vol. 39, Nos. 1–2, 199–211. doi:10.1016/0304-4076(88)90045-0
33. Tam, G. H. F., Chang, C., and Hung, Y. S. (2013). Gene regulatory network discovery using pairwise Granger causality, *IET Systems Biology*, Vol. 7, No. 5, 195–204. doi:10.1049/iet-syb.2012.0063
34. Kim, G., Choi, S.-K., and Seok, J. H. (2020). Does biomass energy consumption reduce total energy CO2 emissions in the US?, *Journal of Policy Modeling*, Vol. 42, No. 5, 953–967. doi:10.1016/j.jpolmod.2020.02.009