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A Longitudinal Study on Deforestation Trends in Indonesia from 1996 to 2022

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Abstract

This study aims to analyse spanning 1996–2022, analyzed deforestation determinants in Indonesia using a Vector Error Correction Model (VECM) to assess short and long-term variable relationships. We focused on GDP per capita, Foreign Direct Investment (FDI), population density, and renewable energy consumption. Results support the Environmental Kuznets Curve (EKC) hypothesis, showing an inverted U-shaped relationship between GDP per capita and deforestation. Deforestation initially increased with economic growth but declined after a turning point of USD 2,443.41 million GDP per capita, around 2009–2010. This suggests that as Indonesia developed, environmental awareness and forest conservation efforts increased. Furthermore, population density and renewable energy consumption significantly reduced deforestation, While FDI had an insignificant positive effect, its impact was statistically irrelevant when considering overall market trends. Policy implications highlight the need for stronger forest governance post-economic development era, to ensure sustainable management, combat illegal activities, and mitigate environmental degradation and have turning point, strict regulation of land-based renewable energy projects, and careful monitoring of investments potentially threatening forest sustainability.

Keywords

Deforestation, Electronic Benefit Transfer, Energy Consumption, Environmental Kuznets Curve.

1. Introduction

The Calvin et al. (2023) found that global surface temperatures in 2011–2020 were 1.1 °C higher than in 1850–1900 due to increased CO_2 emissions. One major contributor to this is deforestation, which not only accelerates climate change but also increases species extinction risk. Kaiho (2023) and public health issues, such as a 4.8% rise in dengue cases per 10% deforestation in Guangdong, China. Studies by Grieco et al. (2024) confirm deforestation's link to rising CO_2 levels. Global net deforestation reached 4.7 million hectares annually from 2010 to 2020, while gross deforestation hit 10 million hectares. In 2015, Brazil, India, and Indonesia were among the top deforesters. Indonesia's deforestation peaked in 1996–2000 due to massive fires during El Niño and the Peatland Project. Although net deforestation has declined since 2011 due to new calculation methods, gross deforestation continues to rise. Between 2020–2021, net deforestation fell by 1.7%, but gross deforestation rose by 16.8%, particularly in primary forests, potentially hindering SDGs progress.

Gultom (2023) analyzed the impact of economic variables consumption, government spending, investment, and net exports on deforestation in Indonesia using panel data from 34 provinces. Lunku et al. (2024) expanded the scope by including forest rent, foreign direct investment, trade openness, rural population growth, agricultural land, and environmental policies. In a follow-up study, Lunku et al. (2025) incorporated electricity consumption, electricity access, and clean cooking fuel access in Sub-Saharan Africa. In Southeast Asia, Destiartono (2023) also included a corruption control index along with economic indicators. However, no research so far has considered renewable energy consumption as a variable influencing deforestation.

A notable example is the biomass project in Papua, where Medco Group cleared rainforest to develop timber plantations as part of Indonesia's transition away from coal. Another case is the global surge in demand for balsa wood, used in wind turbine blades, especially in Europe and China. This demand led to widespread logging of natural balsa forests in the Amazon Basin, severely impacting indigenous communities. Given these dynamics, renewable energy consumption should be considered a significant factor in deforestation studies. Including it would enhance analysis depth and inform more balanced policymaking between clean energy expansion and forest conservation.

Although still limited, several researchers have also studied deforestation using the EKC approach. Some of them are Ajanaku and Collins (2021) in Africa using the GMM panel method from 1990-2016, Lunku et al. (2025) in Sub-Saharan Africa using the DOLS method for 2000-2020, Sohag et al. (2023) in Russia using the one-way autoregressive fixed-effect model for 2009-2019, Destiartono (2023) in Southeast Asia using the Pooled Mean Group (PMG) method for 2000-2020, Adila et al. (2021) in Indonesia using the panel data regression method for 32 provinces in Indonesia for 2013-2016, Kurniawati (2022) in Kalimantan and Sumatra using the panel data regression method for 2010-2017. As far as the author can find, there has been no research examining EKC on deforestation using the VECM method. Therefore, this study contributes to this by analyzing the short-term and long-term causality between deforestation, GDP per capita, GDP per capita squared, foreign direct investment, population density, and renewable energy consumption using the VECM method and the study period 1996-2022.

2. Literature Review

2.1. GDP Percapita, Foreign Direct Investment, and Deforestation

According to Deforestation is defined by Destiartono (2023) as changes in forest cover, further expanded by Dewi et al. (2023) to include reductions in both forest quality (loss of ecosystems) and quantity (decrease in area). Deforestation rates generally follow an inverted J-curve with four stages: pre-transition (low deforestation in poor countries due to limited management), early transition (rapid acceleration from industrialization, common in Southeast Asia, Latin America, and Sub-Saharan Africa since 1990), and post-transition (reduced rates due to improved forest governance, seen in North America and Europe) (Destiartono, 2023). The forest transition concept aligns with the Environmental Kuznets Curve (EKC) framework, proposing a non-linear, inverted

U-curve relationship between development and deforestation. Numerous studies, including Ajanaku and Collins (2021) in Africa, Sohag et al. (2023) in Russia, Adila et al. (2021) in Indonesia, Destiartono (2023) in Southeast Asia, and Lunku et al. (2025) in Sub-Saharan Africa, support this inverted U-curve. Studies by Lunku et al. (2024), Bortolotti et al. (2024), and Destiartono (2023) support a positive correlation between FDI and deforestation. Conversely, the improving pollution hypothesis argues FDI can enhance environmental quality by introducing greener technologies (Subkhan & Hutajulu, 2023) and (Nguyen et al., 2023). Doytch et al. (2024) found a negative correlation between FDI in specific sectors and deforestation globally.

2.2. Population, GDP, Deforestation, and Renewable Energy's Impact

Population density is a significant factor in deforestation. The Neo-Malthusian theory (Obinna, 2021) posits that rapid population growth leads to overexploitation of land, excessive fertilizer use, and increased deforestation, driving the conversion of forest land for residences, agriculture, and infrastructure. A study by Suni et al. (2023) in Kulawi District, Indonesia, found a positive correlation between population density and deforestation. Gatarić et al. (2022) observed that negative demographics, such as depopulation and emigration in South Banat District, Serbia, actually led to increased forest areas through natural regeneration and reforestation, effectively reducing deforestation. However, contradictory findings by Yameogo (2021) in Burkina Faso and Destiartono (2023) in Southeast Asia show a negative correlation between population density and forest area. This can occur when depopulated areas see small-scale farmers selling land to larger agricultural entities. Renewable energy consumption is another crucial aspect of deforestation.

Theoretically, adopting renewable energy aligns with the Environmental Sustainability Theory, which emphasizes clean energy transitions to lessen pressure on natural ecosystems, including forests. Renewable energy serves as an alternative to fossil fuels and traditional biomass, which have historically driven deforestation, particularly in developing countries reliant on firewood, in Ethiopia, Sudan, and Uganda. Increased renewable energy consumption can reduce forest degradation by decreasing community reliance on forest resources for energy. Nan et al. (2023) found that renewable energy significantly reduces the Energy Ecological Footprint (EEF), with a 1% increase in renewable energy cutting EEF by 2.91%. While wind, biomass, and photovoltaic sources contribute differently, wind energy offers the most substantial EEF reduction.

3. Methods

This study uses secondary data in the form of time series data, namely deforestation data, Gross Domestic Product (GDP) per capita, foreign direct investment, population density, and renewable energy consumption in Indonesia for the period 1996-2022. Data sources were obtained from the official World Bank website. Data analysis was carried out using the VECM (Vector Error Correction Model) method using the help of E-VIEWS 12. The VECM long-term equation model can be formulated as follows:

$$DEFt = \beta_0 + \beta_1 GDPKt + \beta_2 GDPK^2t + \beta_3 FDIt + \beta_4 PDt + \beta_5 RECt + et$$

Where, β = intercept, DEF = deforestation (hectares), GDPK = GDP per capita (million USD), $GDPK^2$ = GDP per capita squared (million USD), FDI = Foreign Direct Investment (USD), PD = population density (people per km2), REC = renewable energy consumption, e = error term.

The unit root test is conducted to determine whether a variable is stationary or not, with the commonly used method being the Dickey-Fuller test. If the ADF t-statistic is greater than the critical value at the 5% significance level, the data is considered non-stationary. Conversely, if the ADF t-statistic is less than the critical value or the p-value is below 5%, the data is considered stationary. The determination of the optimal lag is performed to eliminate autocorrelation problems in the VAR system, ensuring that autocorrelation does not reoccur. This is done by comparing the Akaike Information Criterion (AIC) values, and the lag with the smallest AIC is selected as the optimal lag.

The VAR stability test is carried out by calculating the roots of the characteristic polynomial. If all roots have a modulus less than one, the VAR model is considered stable, which ensures the validity of the resulting Impulse Response Function (IRF) and Variance Decomposition (VD) analyses. The cointegration test is essential in the VECM procedure, as the model requires that data be stationary at the first difference level and that a cointegration relationship exists among the variables. This test is conducted by comparing the Trace-statistic with the 5% critical value. If the Trace-statistic exceeds the critical value, cointegration is present. The Granger causality test is used to examine causal relationships among the variables in the model. The purpose of this test is to determine whether an independent variable can improve the forecasting performance of the dependent variable. Model estimation and structural analysis are carried out using the VECM approach, which is like the VAR model. In the VAR framework, structural analysis includes impulse response and variance decomposition. The impulse response analysis is used to observe the impact of a shock or impulse on each endogenous variable, while variance decomposition aims to predict the percentage contribution of each variable to the variance of a particular variable in the system.

4. Results

Test the VECM model, there are several stages that need to be carried out first before the VECM model is obtained. The following are the results of testing these stages. Table 1 show, the result of the unit root test using the Augmented Dickey Fuller (ADF) test. The results of the unit root test indicate that all variables are not stationary at the level because the t-statistic value at the level is greater than the critical value of 5%. Furthermore, a unit root test is carried out at the first difference level. The results of the unit root test at the first difference level indicate that the t-statistics of all variables are smaller than the critical value of 5%, which means that all variables are stationary at the first difference level.

Table 1. Results of the Unit Root Test (Augmented Dickey Fuller Test)

Variable	Level		First Difference		Critical Value in 5 %
	t-statistik	p-value	t-statistic	p-value	
DEF	-2.905278	0.0584	-7.639462	0.0000	-2.981038
GDPK	0.485253	0.9828	-3.795545	0.0085	-2.981038
GDPK2	1.133877	0.9967	-3.348824	0.0232	-2.981038
FDI	-1.218364	0.6507	-6.396910	0.0000	-2.981038
PD	0.124395	0.9610	-3.459588	0.0186	-2.991878
REC	-0.006221	0.9497	-6.021089	0.0000	-2.981038

The optimal lag selection results indicate that Lag 1 is the most suitable choice for the model. This is supported by several criteria: Lag 1 has the highest LogL (Log Likelihood) of -1193.687, indicating a better fit compared to Lag 0 (-1234.601). The LR (Likelihood Ratio) test also favors Lag 1, showing a significant value of 58.91614 (marked with an asterisk indicating significance). Lag 1 boasts the lowest FPE (Final Prediction Error) at 3.78e+35, suggesting superior predictive accuracy. The AIC (Akaike Information Criterion) is lowest for Lag 1 (98.85496), further supporting its optimality. While Lag 0 has slightly lower SC (Schwarz Criterion) and HQ (Hannan-Quinn Criterion) values, the overall strong performance across multiple criteria, particularly LR, FPE, and AIC, points to Lag 1 as the optimal choice.

Table 2. VAR Stability Test Results

Root	Modulus
-0.120024 - 0.469010i	0.484124
-0.120024 + 0.469010i	0.484124
-0.327106 - 0.174074i	0.370540
-0.327106 + 0.174074i	0.370540
0.329221	0.329221
0.098527	0.098527

Table 2 the modulus values of deforestation, GDP per capita, GDP per capita squared, foreign direct investment, population density, and renewable energy consumption are in the range of 0.098527 to 0.484124. Since the modulus value is less than one, it can be concluded that the VAR model is stable.

Table 3. Cointegration Test Results

Hypothesized No of CE (s)	Eigenvalue	Trace Statistic	Critical Value	Prob
None *	0.893273	153.9733	95.75366	0.0000
At most 1 *	0.743847	100.2739	69.81889	0.0000
At most 2 *	0.716767	67.58633	47.85613	0.0003
At most 3 *	0.574459	37.31070	29.79707	0.0056
At most 4 *	0.471939	16.80522	15.49471	0.0316
At most 5	0.059810	1.480161	3.841465	0.2237

Table 3, Trace-statistic value at None, at most 1, At most 2, At most 3, and At most 4 is greater than the critical value with a significance level of five percent with a probability value smaller than the significance of five percent, meaning that there is a cointegration equation. Thus, between the variables GDP per capita, GDP per capita squared, foreign direct investment, population density, and renewable energy consumption have a long-term equilibrium relationship and long-term movement. This also means that the study can be continued using the VECM model.

Table 4. Results of Granger Causality Test

Variable	DEF	GDPK	GDPK2	FDI	PD	REC
DEF	1	0.0085*	0.0531	0.0169*	0.1895	0.8268
GDPK	0.6352	1	0.2877	5.E-05	0.0948	0.0738
GDPK2	0.5824	0.2614	1	0.0007*	0.5272	0.0968
FDI	0.9282	0.0265*	0.0516	1	0.2267	0.7853
PD	0.9140	0.0265*	0.0351	0.0058*	1	0.0037*
REC	0.9244	0.4153	0.2870	0.0146*	0.9065	1

Table 4 explains that based on the results of the Granger Causality test at a significance level of 5%, it shows that there is a relationship that shows a reciprocal relationship between deforestation, GDP per capita, GDP per capita squared, foreign direct investment, population density, and renewable energy consumption. Statistically, there are no variables that affect deforestation. While deforestation has an effect on the variables of GDP per capita and foreign direct investment. Deforestation opens up land for commercial agriculture, mining, and forestry industries such as wood and palm oil. These activities open up investment opportunities and create new jobs that can increase GDP per capita.

Table 5. Short-Term & Long-Term VECM Estimation Results

Estimation	Variable	Coefficient	T-Statistic	T-Table
Short term	CointEq1	-0.004510	-1.35083	2.085963
	DEF (-1)	-0.419330	-2.82039	
	GDPK (-1)	0.001170	1.91227	
	GDPK2(-1)	7.40E-08	0.59421	
	FDI (-1)	-2.66E-11	-1.69082	
	PD (-1)	0.321922	3.04830	
	REC (-1)	0.116048	2.30655	
	C	-0.007008	-0.07972	
Longterm	DEF	1		2.085963
	GDPK	0.203316	6.92243	
	GDPK2	-4.16E-05	-6.72526	
	FDI	8.15E-10	0.91356	
	PD	-26.09830	-5.51461	
	REC	-17.31527	-5.55729	
	C	17.24778		

Table 5 show short-term VECM estimation results above shows that at lag 1, the GDP per capita and GDP per capita squared variables have an insignificant positive effect on deforestation because the t-statistic value < t-table. The FDI variable has an insignificant negative effect on deforestation because the t-statistic value < t-table. Meanwhile, the population density and renewable energy consumption variables have a significant positive effect on the deforestation variable because the t-statistic value > t-table. The long-term VECM estimation results indicate that all independent variables, except Foreign Direct Investment (FDI), have significant t-statistics at the 5% level. GDP per capita (GDPK) has a positive and significant coefficient (β = 0.203316), while its squared term (GDPK2) is negative and significant (β = -4.16E-05). This confirms the Environmental Kuznets Curve (EKC) hypothesis, where deforestation increases with income up to a turning point of USD 2,443.41 million, after which it begins to decline. FDI has a positive but insignificant coefficient (β = 8.15E-10), suggesting a minimal effect on deforestation. Population density (PD) significantly reduces deforestation, with a coefficient of β = -26.09830, meaning an increase of 1 person/km^2 is associated with a decrease in deforestation by 26.10 hectares, ceteris paribus. Renewable energy consumption (REC) also has a negative and significant effect (β = -17.31527), indicating that a 1% increase in renewable energy use reduces deforestation by 17.31 hectares.

The estimation of the Impulse Response Function (IRF) is used to analyze how deforestation reacts to shocks in several variables over time and how long these effects persist. The horizontal axis in the IRF graph represents time, with one period equivalent to one year, and the study spans 20 periods. A shock to GDP per capita generates a positive response in deforestation, which lasts for 10 periods before stabilizing. In the case of GDP per capita squared, deforestation also responds positively, although exceptions occur in periods 4 and 7. The effect of this shock persists until period 12 before returning to equilibrium. Meanwhile, a shock from foreign direct investment (FDI) results in a negative trend in deforestation, with the effect lasting up to 10 periods before stabilizing. A population density shock initially causes a negative response in the first two periods, but a positive trend emerges afterward, stabilizing from period 8. Renewable energy consumption triggers a positive response in the first two periods, turns negative in period 3, and then trends positively again, reaching equilibrium around period 12.

Table 6. Results of the Variance Decomposition Test

Period		DEF	GDPK	GDPK2	FDI	PD	REC
1	0.428384	1.000.000	0.000000	0.000000	0.000000	0.000000	0.000000
2	0.648057	4.397.253	3.564.504	0.234534	2.838.930	0.072025	1.723.694
3	0.740567	4.732.676	2.797.166	5.427.630	3.797.432	1.160.964	1.431.556
4	0.826044	4.279.900	3.239.352	8.512.244	3.502.486	0.934765	1.185.798
5	0.864692	4.288.737	3.173.834	8.918.182	3.926.339	1.185.497	1.134.428
6	0.916250	4.305.756	4.325.578	8.127.674	4.027.105	1.055.975	1.066.784
7	0.956853	4.224.425	3.461.128	7.496.672	4.572.663	1.221.655	9.853.484
8	0.995645	4.354.153	3.430.882	7.058.948	4.551.832	1.181.582	9.357.284
9	1.035.381	4.280.557	3.571.243	6.535.996	4.797.266	1.143.600	9.005.140
10	1.070.351	4.325.578	3.587.697	6.178.443	4.960.539	1.175.487	8.552.779
11	1.106.267	4.328.739	3.649.105	5.791.576	5.046.299	1.144.971	8.238.716
12	1.139.449	4.331.857	3.690.164	5.492.860	5.191.357	1.153.988	7.941.589
13	1.172.603	4.347.481	3.722.472	5.213.789	5.269.820	1.139.985	7.676.872
14	1.204.545	4.345.959	3.763.266	4.956.416	5.374.188	1.138.030	7.439.123
15	1.235.533	4.358.611	3.787.164	4.737.372	5.447.478	1.133.957	7.223.437
16	1.266.048	4.360.124	3.818.637	4.528.683	5.521.684	1.127.254	7.034.771
17	1.295.569	4.366.530	3.841.700	4.345.383	5.590.657	1.125.888	6.855.767
18	1.324.623	4.371.205	3.864.796	4.174.273	5.648.196	1.120.640	6.696.886
19	1.352.944	4.374.636	3.886.062	4.018.721	5.706.443	1.118.328	6.549.533
20	1.380.727	4.379.290	3.904.619	3.875.788	5.756.157	1.114.983	6.413.987
21	1.407.965	4.382.189	3.922.948	3.742.840	5.804.272	1.112.224	6.289.288
22	1.434.660	4.385.887	3.938.947	3.620.710	5.847.931	1.109.850	6.173.164
23	1.460.897	4.388.749	3.954.427	3.506.542	5.888.520	1.107.252	6.065.934
24	1.486.647	4.391.620	3.968.563	3.400.621	5.926.736	1.105.225	5.965.586
25	1.511.974	4.394.329	3.981.803	3.301.580	5.961.888	1.103.049	5.872.168
26	1.536.877	4.396.732	3.994.271	3.208.907	5.995.210	1.101.168	5.784.681

The variance decomposition analysis presented in Table 6 reveals that deforestation is initially influenced primarily by its own past values. Over time, however, the influence of external variables increases. GDP per capita's impact on deforestation fluctuates in the first eight periods but consistently grows afterward, ultimately contributing 39.94% to the variance in deforestation by the 26th period, making it the most dominant explanatory factor. GDP per capita squared peaks in influence by period 5 before gradually declining. FDI shows a steadily increasing effect, while the influence of population density and renewable energy consumption diminishes over time, though the decrease in impact from population density remains relatively small.

5. Discussion

This study found an inverted U-shaped relationship between GDPs per capita and deforestation, supporting the Environmental Kuznets Curve (EKC) hypothesis. Initially, a 1 million USD increase in GDP per capita raises deforestation by 0.203316 hectares. However, after a turning point of USD 2,443.41 million, observed around 2009–2010, increased income correlates with reduced deforestation. This period coincides with significant Indonesian environmental policies, including a 2009 emission reduction commitment and the 2010 REDD+ partnership in Norway by Destiartono (2023), leading to a 2011 moratorium on new permits in primary forests and peatlands. A general downward deforestation trend has since appeared by Austin et al. (2019), also linked to an economic shift towards less land-intensive industrial and service sectors. This supports Adila et al. (2021) and indicates that economic welfare can reduce pressure on forests with strong environmental governance. The study also identified a positive relationship between Foreign Direct Investment (FDI) and deforestation, aligning with the Pollution Haven Hypothesis. This suggests foreign investors may favor Indonesia due to potentially looser environmental regulations, with FDI entering high-risk sectors like mining, forestry, and oil palm.

This direction, though not statistically significant, is consistent with Lunku et al. (2024), Bortolotti et al. (2024). Conversely, population density showed a negative correlation with deforestation in Indonesia, contradicting Neo-Malthusian theory. This could be because densely populated areas may have already converted most forest land, leaving less available for new deforestation. Additionally, population growth can spur technological and institutional advancements that reduce forest pressure. This finding is consistent with Yameogo (2021) and Destiartono (2023). Finally, a negative relationship was found between renewable energy consumption and deforestation. Increased renewable energy use, through household biogas, solar panels, and efficient stoves, reduces reliance on firewood, a direct driver of deforestation.

Renewable sources like rooftop solar and small-scale microhydro systems offer a significant advantage by circumventing the need for extensive land conversion. Unlike large-scale power plants or even some forms of renewable energy, these technologies integrate seamlessly into existing environments. Rooftop solar, for instance, utilizes pre-existing structures, transforming unused space into energy-producing assets without encroaching on valuable land. Similarly, small-scale microhydro systems are designed to harness the power of existing water flows, minimizing their footprint and avoiding the displacement of natural habitats or agricultural areas. This inherent characteristic makes them particularly attractive for sustainable development, as they contribute to energy generation without demanding new land clearing or significant habitat disruption. Examples in Indonesia include the Centralized Solar Power Plant (PLTS) Installation and Rooftop PLTS programs in remote areas like East Nusa Tenggara, Papua, and North Kalimantan, and the 2021 Ministry of Energy and Mineral Resources and GIZ Germany's EnDev project for household biogas and efficient biomass stoves in NTB and NTT

6. Conclusion

This study concludes that deforestation in Indonesia is significantly influenced by economic growth, renewable energy consumption, and population density, following a pattern consistent with the Environmental Kuznets Curve (EKC) hypothesis. The policy implications of these findings include the strengthening of forest governance, where moratorium policies and incentives for forest conservation need to be reinforced, especially after reaching the economic turning point. In addition, regulations related to renewable energy must ensure that developed projects do not lead to forest land conversion, with a focus on technologies that require minimal land use, such as rooftop solar panels. Monitoring of Foreign Direct Investment (FDI) is also crucial, particularly in land-based sectors such as mining and plantations, to prevent uncontrolled increases in deforestation.

The limitation of this study lies in the use of national aggregate data, which may not capture regional variations. Therefore, future research is encouraged to use spatial data or qualitative approaches to better understand local dynamics. Thus, this study provides an empirical basis for formulating more balanced policies between economic development and environmental sustainability. This study has limitations, including the use of national aggregate data that may mask regional variations and the failure to account for factors such as climate change. Policy implications include the need to strengthen forestry regulations, adjust renewable energy regulations to prevent land conversion, and improve monitoring of foreign investment. Future research suggests using a more detailed spatial approach, qualitative approaches through interviews with local stakeholders, and longitudinal analysis studies to provide policy effectiveness and better understand the dynamics between economic growth and environmental desires.

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