WWJMRD 2024; 10(06): 34-44
www.wwjmrd.com
International Journal
Peer Reviewed Journal
Refereed Journal
Indexed Journal
Impact Factor SJIF 2017: 5.182 2018: 5.51, (ISI) 2020-2021: 1.361
E-ISSN: 2454-6615

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Exploring the Environmental Kuznet Curve Evidence from ARDL Analysis of GDP, Forest Area, and CO2 Emissions in the Philippines

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Abstract
This study investigates the relationship between economic growth (GDP), forest area cover, and CO2 emission using the Autoregressive Distributed Lag (ARDL 2,1) approach to analyze the short and long-term interaction among these variables. Using time series data from 1990 to 2020 from the World Bank Development Indicator, the ARDL model provides insights into the complex interplay between economic development and environmental sustainability. In the case of the Philippines, the findings reveal a significant relationship between GDP, forest cover, and CO2 emissions, with both short and long-run effects observed. Significantly, the model suggests a positive short-term association between economic growth and CO2 emissions, aligning with the early stage of the Environmental Kuznet's Curve (EKC) and, in the long run, a negative relationship confirming the latter phase of the EKC hypothesis where pollution decline as economies mature and prioritize environmental regulations. Also, the model identifies a negative short-term impact of economic growth on forest area cover, underlining the pressure of resource consumption and land conversion in the initial stages of development. Moreover, the study presents a potential negative long-run effect of deforestation on CO2 emissions, underscoring the critical role of forests in carbon sequestration and climate change mitigation. These findings contribute to the ongoing discourse on sustainable development and environmental policy-making, emphasizing the importance of integrated approaches that balance economic growth with ecological conservation goals.

Keywords: Economic Growth, CO2 Emissions, Forest Area Cover, Environmental Kuznet Curve (EKC), Autoregressive Distributed Lag (ARDL), Philippines, UN SDG 13.

1. Introduction

The United Nations reported that global heat records have been repeatedly smashed in recent years. In 2023, the average near-surface temperature was 1.45ºC above pre-industrial levels, dangerously close to the critical 1.5-degree threshold set in the 2015 Paris climate accords (Larson, n.d.). The period from February 2023 to January 2024 recorded the first time temperature endured 12 consecutive months of temperature 1.5o hotter than the pre-industrial period. February sustained the record-breaking stretch, averaging 1.77o warmer compared to the monthly estimate for the 1850-1990 benchmark (Carbon Emissions and El Nino Push Oceans to Record Temperatures, n.d.). The Philippines experienced scorching weather attributed to El Niño in 2024, with temperatures reaching record highs. The index heat, which accounts for relative humidity, stayed at a record 45, a range classified as dangerous due to the greater risk of heatstroke (Reuters, 2024).

Carbon emissions as a consequence of burning fossil fuels are the result of global warming and climate change. Measuring carbon emissions is vital for evaluating their environmental impact, developing projects to alleviate their effect, and recommending policy decisions on climate change. Carbon emission is a negative externality wherein the social cost of emission is not fully reflected in the market prices. Investigating carbon emissions helps experts understand the degree of this market failure and recommend strategies, such as a cap-and-trade system or carbon pricing, to internalize this external cost. Consumption and production patterns are closely linked to carbon emissions, providing insights into the efficiency of resource allocation, energy intensity, and potential for transitioning to cleaner and more sustainable energy resources.

In the Philippines, the average per capita CO_2 depicts how much carbon dioxide an average person emits based on production-based emissions that do not account for traded goods (Ritchie & Roser, 2020). Approximately the Philippines emits 1.18 metric tons of CO_2 per person. In terms of annual emissions, the Philippines produced 126,922,622 tons of CO_2, representing emissions from burning fossil fuels and production within its borders. Over the previous years, CO_2 emissions increased by 12.3%, adding nearly 14 tons (Worldometer, 2016). In the year-on-year growth each year, factors such as economic activity influenced the annual CO_2 emission (Ritchie & Roser, 2020). The Philippines is committed to reducing its greenhouse gas (GHG) emission by about 70% relative to its Business As Usual (BAU) scenario from 2000 to 2030, coming from various sectors, including energy, transport, waste, forestry, and industry (Ranada, 2015). In terms of energy intensity, monitoring is critical for evaluating development in emission reduction. Decreasing energy intensity can lead to more efficient energy use and reduce emissions per unit of energy produced (Ritchie & Roser, 2020). Further, the Philippines is interested in exploring carbon pricing mechanisms to incentivize emission reductions since the average Net Effective Carbon Rate (Net ECR) on GHG emissions has increased significantly since 2018, showing efforts to improve climate change (Carbon Pricing in the Philippines, n.d.).

Historically, there is a significant positive link between the Gross Domestic Product GDP and carbon emissions. As countries increase their production output, CO_2 tends to increase, which is specifically common in low-to-middle-income countries (Archer, 2018). Energy consumption is the reason behind the correlation attributed to growing economies that consume more energy, often burning fuel as the primary source, releasing CO_2 into the environment. However, there is a positive development among many countries decoupling economic growth from CO_2 emissions, which achieved economic prosperity without increasing emissions. They successfully reduced their carbon intensity (CO_2 emission per unit of GDP) using cleaner technologies, improving energy efficiency, and transitioning to renewable energy sources (Carbon Emission Intensity of Economies, n.d.). A lower carbon intensity means less CO_2 is emitted when producing a given level of economic output, indicating a more carbon-efficient economy. While reducing emissions, these countries with lower carbon intensity are better at attaining economic growth, balancing development and environmental impact (European Commission, 2022).

Forests are central in carbon sequestration, absorbing carbon dioxide from the atmosphere during photosynthesis and storing it as carbon stocks in vegetation, soil, and trees. Deforestation releases these stocks back into the atmosphere as carbon emissions. In a study by Mitiku Badasa Moisa et al. (2023) on the effects of forest cover change on carbon stocks, emissions, and land surface temperature (LST). Over three decades wherein, the forest land declined by 336.6 km2 attributed to agricultural expansion, causing carbon stock to decrease by 58,883.4 tons/km2 while the carbon emission increased by 2,418,083.91 tons over the same period with declining vegetation LST increased by an average of 3.7oC, highlighting the need for tree planting and reforestation program to mitigate rising LST and carbon emission. Forests worldwide assume the role of a carbon sink, scrubbing approximately 2 billion metric tons of carbon from the atmosphere annually (European Commission, 2022). However, deforestation and forest degradation add to direct greenhouse gas (GHG) emissions, worsening climate change. A complex relationship exists between forest cover and carbon emission; afforestation can counterweight emissions. High-income countries with low forest cover focus on afforestation, while low-income countries experience deforestation. Forest cover positively correlates with carbon emissions in the short term (Beaty, n.d.).

A central challenge arises in attaining sustainable development and balancing economic growth with environmental protection. This research investigates the relationship between carbon emissions (endogenous variable), Gross Domestic Product (GDP), and forest cover area (exogenous variables) to gain insight relevant to environmental economics. Specifically, the study aims to establish the empirical relationship between economic growth and carbon emissions in the Philippines. Understanding this link is crucial for formulating policies that promote economic development while minimizing environmental impact, measuring if the higher level of GDP necessarily leads to increased carbon emissions. The forest acts as a carbon sink, absorbing CO_2 from the atmosphere; the objective seeks to quantify the influence of forest cover area on carbon emissions, measuring if a larger forest area leads to a measurable reduction in carbon emission.

The findings from this research contribute to the broader understanding of the factors driving carbon emissions and the potential for mitigating climate change. In quantifying the relationship between economic activity, forest cover, and carbon emission, the information generated from this study helps to inform the development of several key environmental and economic policies.

2. Theoretical Framework

Major The Environmental Kuznets Curve (EKC) hypothesis is a prominent theory in environmental economics that explores the relationship between economic development (GDP) and environmental degradation, often measured by pollutant concentrations (Kong & Khan, 2019), (Özokcu & Özdemir, 2017), (Shahbaz et al.,2013), (Dinda, 2004). It proposes an inverted U-shaped relationship, where environmental degradation initially deteriorates with economic growth but eventually improves as countries attain higher income levels (Haider et al.,2023), (Lin-Sea et al., 2023), (Liton et al.,2023). This research, focusing on carbon emissions (endogenous variable) and its link with GDP (exogenous variable), benefits from incorporating the EKC hypothesis while considering the role of forest cover area (exogenous variable).

The most intensively studied pollutant is CO_2 (Lajunen & Lipman, 2016), (Talukdar & Meisner, 2001), (Sarkodie & Strezov, 2018), composing 76% of the total greenhouse gases emitted (Malyan et al., 2019). Experts employ a multivariate framework to address the unidentified variables and integrate several independent variables other than GDP (Sarkodie & Ozturk, 2020), (Ardakani & Seyedaliakbar,2019), (Huang et al., 2022). These factors contribute to understanding the causal effect of CO2 emissions while assisting in re-examining the validity of the EKC hypothesis (Liu, 2020), (Leitão et al., 2021). The variables include energy consumption (Usman et al., 2019), trade openness (Koc & Bulus, 2020), and foreign direct investment (Ochoa-Moreno et al., 2021). Following this, this study selects the combinations of GDP and forest cover variables to test the EKC hypothesis in the Philippines. Each variable has vital economic implications relevant to CO2 emissions.

The link between economic growth and carbon emission is examined in several studies, furnishing mixed evidence that the relationship between CO2 emission and GDP growth is negative or initially positive and eventually negative (Muftau et al., 2014), (Narayan et al., 2016), (Khan et al., 2023), (Nawaz et al., 2021), (Le, 2019).

Other studies convey instead a positive relationship. More recent research used the autoregressive distributed lag (ARDL) model and a nonlinear variety to examine the relationship between economic growth and CO2 emission and determine a positive long-term relationship between the two variables (Sikder et al., 2022) (Akalpler & Hove, 2019). The environmental Kuznet Curve (EKC), depicted as the inverted U-shaped curve Kuznets (Naveed et al., 2022) used to model the association between CO2 and economic growth, has become a common framework to investigate the linkage in a country (Liu, 2020) (Yao et al., 2019), (Hasanov et al., 2019). Some studies presented mixed results, with some studies supporting the existence of an EKC (Zhang et al., 2019), others found no significant relationships (Alam et al., 2016)., and others reporting an N-shaped relationship (Narcisse et al., 2023). The broad spectrum of findings is attributed to the various pollution indices, sample period used, estimation techniques, and model specifications.

In an attempt to reduce the emission of carbon or scrub carbon from the atmosphere, forests come primarily (Koirala & Mysami, 2015). Researchers conducted a study to verify whether forests best reduce carbon by supplying wood as a substitute for fossil fuel or reducing carbon by absorbing it (Yao et al., 2019). Notably, using wood as a substitute for fossil fuel is lower than forests' carbon reduction potential. However, a forest fire emits carbon and many other dangerous gases in the air (Koirala & Mysami, 2015). Moreover, carbon emissions are associated with forest deterioration, deforestation, and wood harvest (Sarkodie, 2018).

The Carbon Absorption of trees in the tropics forest depends on several factors, including environmental conditions and biodiversity (Altıntaş & Kassouri, 2020). Data suggest that a significant increase in forest cover area improves carbon emission and energy efficiency. Thus, afforestation is an outstanding strategy for addressing climate change's challenges (Caravaggio, 2020). While significant studies evaluate the effect of forests on climate, it was observed that increased temperature negatively affects trees in terms of productivity, growth, and potential (Raihan & Tuspekova, 2022). Hence, the carbon absorption of trees diminishes due to adverse climate change (Tsiantikoudis et al., 2019).

Fewer studies investigate the role of forest activities in reversing environmental externalities (Cowie et al., 2007). Several studies attempted to identify the role of the forest. However, they did not differentiate between forest coverage, management, and investment, providing more insight into the forest environment. Several techniques exist to sequester carbon from the atmosphere or reduce carbon emissions; a forest comes first. Whether the forest is managed for energy plantation or carbon storage, there was a notable reduction in carbon emissions (Sasaki et al., 2016).

3. Methods

This study used data retrieved from the World Bank's World Development Indicators. The annual data represents the Philippines from 1990 to 2020. The model comprises variables such as CO_2 Emissions in Million Metric Tons, GDP in billion US$, and Forest cover as % total land area. The Autoregressive Distributed Lag (ARDL) model is the appropriate econometric method to evaluate the relationship between variables in a time series data. This study intends to determine the relationship between GDP, Forest area cover, and CO2 emission based on the Environmental Kuzents Curve (EKC) hypothesis.

Table 1 below presents the Augmented Dickey-Fuller (ADF) unit root test result at first differencing from the three-time series data: Forest_area, GDP, and CO2_emission. The ADF statistics and the corresponding p-value displayed the critical values for rejecting the null hypothesis of a unit root at 1%, 5%, and 10% significance levels. The ADF statistic for Forest_area of -4.24501 ($p<0.001$) indicates a stationary time series; for CO2_emission result of -3.60569 ($p<0.001$), infer that it is also stationary. The case for GDP is less clear-cut with -3.1008 ($p<0.05$). Though lower than the critical value of 0.05, it exceeds the stricter 1% threshold. The result suggests that all variables exhibit stationarity, implying that their mean and variance remain constant over time, and their future values are not solely determined by their past values, paving the way for further analysis into the potential long-run equilibrium relationship between them.

Table 1: ADF Test Results.

	Forest_area	**GDP**	**CO2_emission**
ADF Statistic	-4.24501	-3.1008	-3.60569
p-value	0.00055	0.02698	0.00556
Critical Value (1%)	-3.66198	-3.66198	-3.66198
Critical Value (5%)	-2.96054	-2.96054	-2.96054
Critical Value (10%)	-2.61932	-2.61932	-2.61932

Table 2 compares AIC (Akaike Information Criterion) and BIC (Bayesian Information Criterion) values for ARDL (autoregressive Distributed Lag) model specification. The ARDL model is an econometric method for examining relationships among stationary variables to determine the relationship between variables with different lags (Kripfganz & Schneider, 2023). The AIC and BIC are two model selection criteria commonly used to determine the optimal lag period in ARDL models. The complexity of the model is penalized on a likelihood function based on AIC, while BIC is based on Bayesian theory and imposes a high penalty on model complexity (Kalmaz & Kirikkaleli, 2019).

Table 2: Comparison of ARDL Model Fit using AIC and BIC:

	Model Specification	AIC	BIC
0	ARDL (2,2)	1009.63	1021.46
1	ARDL (2,1)	1007.93	1017.35
2	ARDL (1,2)	1007.52	1016.94
3	ARDL (1,1)	1012.71	1018.92

The ARDL model specifications in the table differ in the number of lags of the dependent and independent variables. The IAC and BIC are calculated for each model, and the model with the lowest AIC or BIC values is considered the best fit (Kripfganz & Schneider, 2016, July). Based on Table 2, the AIC value of the ARDL (2,1) model is relatively lower, indicating a good fit among the comparable models. However, the ARDL (1,1) model presents the lowest BIC value, conveying that it is the most parsimonious model (Kripfganz & Schneider, 2023). Since this study focuses on prediction and model fit, the ARDL (2,1) was preferred (Hamid & Shabri, 2017).

The ARDL (2,1) model includes two lagged values of the dependent variable (CO2 emissions), one lagged value of the independent variable (forest area cover), and two lagged values of another independent variable (GDP). The coefficient ($\beta1$ to $\beta7$) represents the relationship between the variables, and the error term (εt) captures the random variation in the data (Ponce et al., 2021). The ARDL (2,1) estimates the long-term relationship between CO2 emission, GDP, and forest area cover (Ngarava, 2021). The lagged variables' coefficients (CO2t-1, GDPt-1, GDPt-2, and Forest_area_covert-1) determine the long-term relationship between the variables. The coefficient of the first differences (ΔCO2t, ΔGDPt, and ΔForest_area_covert) are used to determine the short-term relationship between variables (Raihan, 2023).

The ARDL (2,1) model is a valuable technique for examining the relationship between CO2 emissions and GDP and forest area cover, allowing for the estimation of both short-term and long-term relationships between variables handling endogeneity and serial correlation in the data (Muhammad Daniyal et al., 2023). However, selecting the appropriate lag length is crucial for the model's validity, and the model is sensitive to the choice of the lag length. Therefore, careful consideration was attributed to the choice of lag length in the ARDL (2,1) model (Ngarava, 2021).

The ARDL (2,1) is expressed in the equation below.

$$\Delta CO2t = \beta0 + \beta1\Delta GDPt + \beta2\Delta GDPt\text{-}1 + \beta3\Delta Forest\_area\_covert + \beta4CO2t\text{-}1 + \beta5GDPt\text{-}1 + \beta6GDPt\text{-}2 + \beta7Forest\_area\_covert\text{-}1 + \varepsilon t \quad (1)$$

Where

ΔCO2t is the change in CO2 emission at time t
ΔGDPt is the change in GDP at time t
ΔGDPt-1 is the change in GDP at time t-1
ΔForest_area_covert is the change in forest cover area at time t
CO2t-1 is the lagged value of CO2 emissions at time t-1
GDPt-1 is the lagged value of GDP at time t-1
GDPt-2 is the lagged value of GDP at time t-2
Forest_area_covert-1 is the lagged value of the forest area cover at time t-1
εt is the error term at time t

Generally, following the result of the data analysis above, the present study explores the effect of economic growth and forest cover area on carbon emission in the Philippines, considering the heterogeneity, serial correlation, and endogeneity issues in the generated model. Such analysis allows for measuring the significant effect of the exogenous variables on carbon emission.

4. Results & Discussion

The objective of this study is to investigate the relationship between carbon emission (endogenous variable) and GDP and forest cover (exogenous variables) using the Autoregressive Distributed Lag (ARDL), examining the validity of the EKC hypothesis, which infers an inverted U-shape relationship between the dependent and independent variables. Also, this study seeks to explore the possible mitigating effect of forest cover on carbon emission, as forests act as carbon sink, absorbing and storing CO2. The ARDL was used to capture both the short and long-run dynamics of the relationships between the variables while accounting for the validity of the generated model.

Table 3 presents summary statistics for three variables: CO2 emissions (Million Metric Tons), GDP (billion US$, and Forest cover (%total land area). The average value for CO2 is 90.6 million metric tons, while the median is also 90.6, indicating a symmetric distribution, and the standard deviation (20.91188) shows a moderate level of dispersion around the mean. The minimum value for CO2 emission is 56.1 million metric tons, and the maximum is 125.1 million metric tons. For GDP, the mean is $204.9035 billion, with a median of $179.3658 billion, suggesting a slightly positive skewed distribution, and the standard deviation ($89.35478) indicates a relatively high level of GDP variability. Regarding the Forest cover, the average is 24.21334%, and the median is 23.99202%, conveying a comparatively symmetric distribution and the standard deviation (0.932718) showing a low level of dispersion.

Table 3: Descriptive statistics. Average values across the time 1990–2020.

	CO_2 Emissions (Million Metric Tons)	GDP (billion US$)	Forest cover (% total land area)
Mean	90.6	204.9035	24.21334
Median	90.6	179.3658	23.99202
Standard Deviation	20.91188	89.35478	0.932718
Minimum	56.1	106.6417	22.93899
Maximum	125.1	396.2244	26.08851

Table 4 summarizes the result of the Ordinary Least Squares (OLS) regression analysis where CO2_emission is the dependent variable, and GDP and forest_area are explanatory variables. The model exhibits an exceptionally high R-squared value of 0.999, indicating 99.9% of the variation in CO2 emission, which is explained by the independent variables, the GDP and fores_area. The adjusted R-squared, which adjusts for the number of explanatory variables, is also very high (0.999), suggesting that the model effectively captures the relationship between the variables while avoiding overfitting. The F-statistics of 1.61e+04 and its incredibly small corresponding p-value (2.91e-43) imply that the model statistically fits the data exceptionally well. The regression coefficient of GDP and forest_area are jointly statistically different from zero, indicating that they significantly influence CO2 emissions.

Table 4: Result of the Ordinary Least Square (OLS) regression analysis.

Dep. Variable:	**CO2_emission**	**R-squared**	**0.999**
Model:	OLS	Adj. R-squared	0.999
Method:	Least Squares	F-statistics	1.61e+04
No. of Observations:	29	Prob (F-statistic):	2.91e-43
Df Residuals:	24	Log-Likelihood	-47.245
DF Model:	4	AIC	104.5
		BIC	111.7

Table 5 presents the estimated coefficients, standard errors, t-statistics, p-values, and confidence intervals for a regression model. The estimated coefficient for the constant term is -217.7971, which presents the expected level of CO2 emission when all other explanatory variables are zero. However, due to the potential endogeneity of CO2 emissions, interpreting the constant term in isolation is not meaningful. The model shows two lagged dependent variables, CO2_emission_lag1 and CO2_emission_lag2. The positive and statistically significant coefficient (1.5499) for CO2_emission_lag1 indicates that past CO2 emission levels positively influence current emissions due to factors like inertia in emission reduction policies or technological advancements. The negative and statistically significant coefficient (-0.5591) for CO2_emission_lag2 suggests a dampening effect of past emissions on current levels.

Table 5: Estimated coefficients, standard errors, t-statistics, p-values, and confidence intervals for the Regression model.

	coef	**Std err**	**t**	**P>[t]**	**0.025**	**0.975**
const	-217.7971	11.096	-19.630	0.000	-241.638	-193.956
CO2_emission_lag1	1.5499	0.093	16.724	0.000	1.357	1.743
CO2_emission_lag2	-0.5591	0.099	-5.666	0.000	-0.763	-0.355
GDP_lag1	-0.0004	6.23e-06	-63.874	0.000	-0.000	-0.000
Forest_area_lag1	-0.0104	0.005	-2.078	0.048	-0.021	-0.000

The coefficients for two explanatory variables, GDP_lag1 (lagged GDP) and Forest_area_lag1 (lagged forest area cover), are of primary interest. The statistically significant negative coefficient (-0.0004) for GDP_lag1 suggests that higher economic activity (GDP) is associated with lower CO2 emission, possibly due to technological advancements or policy interventions. Nevertheless, these findings need to be interpreted cautiously due to the potential endogeneity of CO2 emissions. Similarly, the negative and marginally significant coefficient (-0.0104) for Forest_area_lag1 claims a potential negative association between forest cover and CO2 emissions, which aligns with expectations. However, the marginal significance (p-value = 0.048) suggests that further investigation is needed to confirm this relationship.

The endogeneity of CO2 emissions complicates the interpretation of these results. If factors influencing CO2 emissions also influence GDP or forest cover, the estimated coefficient might be biased and not reflect the causal relationship, requiring a more careful interpretation.

Table 6 displays the results of diagnostic tests employed to assess the normality of the error terms and the presence of serial correlation in the regression model. The Omnibus test statistic (1.122) and Jacque-Bera (JB) statistic (1.035) are presented along with their corresponding p-values (0.571 and 0.596, respectively). Since both p-values have a greater significance of 0.05, it conveys that the model's residuals do not deviate significantly from a normal distribution. The Durbin-Watson statistics (1.858) is diagnostic for the residuals' autocorrelation (serial correlation). However, the Durbin-Watson test is inconclusive for models with lagged dependent variables, as in this case. However, the value falls within the inconclusive range between 1.5 and 2.5. It did not furnish definitive evidence for or against serial correlation.

Table 6: Normality of error terms and Serial correlation test.

Omnibus	1.122	**Durbin-Watson**	1.858
Prob (Omnibus):	0.571	Jarque-Bera (JB)	1.035
Skew:	0.408	Prob (JB)	0.596
Kurtosis:	2.632	Cond. No.	4.92e+08

Depicted in Table 7 is the Hansen J-test, which measures whether the instrument used in the IV estimation is valid with a test statistic of 0.36087 and a p-value of 0.547336. Since the p-value is greater than 0.05, it conveys that the instruments are valid and uncorrelated with the error term. Also, the Sargan-Hansen test checks the validity of the instruments, presenting the result of test statistics as 2.86595, and the p-value is 9.00182e-05, indicating that the instruments are valid.

Table 7: Instrument Validity Test.

Common Instrumental Variable (IV) Approach Test	Statistic	p-value
Hansen J-Test for Over Identification	0.36087	5.47336e-01
Sarga-Hansen Test for Instrument Validity	2.86595	9.00182e-05

Table 8 displayed the result of the Wald statistics of 20847.3, one degree of freedom, and a p-value of 0, which indicate that the null hypothesis that all the regression coefficients (except the intercept) are jointly equal to zero – is unlikely to be true. The model with the included explanatory variables (GDP and forest_area) is statistically significant in explaining CO2 emissions compared to a model with only the intercept. The high Wald statistics suggest that at least one of the explanatory variables (GDP or forest_area) has a statistically significant effect on CO2 emission. However, it did not pinpoint which specific variable was significant or the direction of the causal effects. The Likelihood Ratio test (LRT) was used to determine the likelihood of the entire model with all parameters estimated to the likelihood of a reduced model with some parameters fixed or restricted, evaluating whether the additional parameters in the full model significantly improve the fit. LRT is asymptotically equivalent to the Wald test and is often preferred due to its robustness to anomalies (Wilks et al., 2020). The LR statistics is 17.5072 with a p-value of 0.000568. A larger LR statistic and a smaller p-value (less than 0.05) convey stronger evidence favoring the unrestricted model. Including Forest cover and GDP as exogenous variables significantly improves the model fit compared to the restricted model with only CO2 emissions. Thus, evidence suggests that the two exogenous variables significantly explain CO2 emissions in the long run.

Table 8: Wald Statistics Result.

Wald Statistic	20847.3	LR (Likelihood Ratio) Statistics	17.5072
Degrees of Freedom	1	p-value	0.000568
p-value	0		

The Trace test in Table 9 checks the long-run relationship (cointegration) between the variables. The Test statistics (24.1961) are compared to critical values at different significance levels (1%, 5%, and 10%), depicting the test statistic as less than the critical value at the 1% level (24.1961 < 37.0339), rejecting the null hypothesis of no cointegration implying the presence of a long-run relationship between variables. Similarly to the trace test, the max eigenvalue test also evaluates cointegration. The test statistic (15.0356) is compared to critical values exceeding the critical value at the 1% level (15.0356 < 28.5845) that rejects the null hypothesis of no cointegration.

The significance levels (0 and 1) indicate the p-values associated with the test. For the trace test, the p-value is 0 (highly significant), confirming cointegration; for the max eigenvalue test, the p-value is 1 (not significant (which contradicts the test result. This discrepancy is due to the small sample size. Further investigation was conducted to check and validate the cointegration result using the Bootstrap cointegration test.

Table 9: Bounds Test Result.

Test Statistic (Trace)	24.1961
Critical Value (Trace) 1%	37.0339
Critical Value (Trace) 5%	31.2379
Critical Value (Trace) 10%	28.1445
Significance (Trace)	0
Test Statistics (Max Eigen)	15.0356
Critical Value (Max Eigen) 1%	28.5845
Critical Value (Max Eigen) 5%	24.7847
Critical Value (Max Eigen) 10%	22.2516
Significance (Max Eigen)	1

The result from the CO2 emission with exogenous variables in Bootstrap Cointegration Test in Table 10, the p-value associated with the constant term is 0.504, expressing that the constant term is not statistically significant in the cointegration relationship. The p-value for the forest area variable is 0.002, indicating that the variable is statistically significant in the cointegration relationship. Similarly, the p-value for the GDP variable is 0.000138, showing a cointegration relationship.

Table 10: Bootstrap Cointegration Test.

Variable	Bootstrap Cointegration Test p-value
const	0.504
Forest_area	0.002
GDP	0.000138

Table 11 shows the result of the Granger causality test conducted to investigate the causal relationships between CO2 emission, GDP, and Forest_Cover displaying the p-values for lags 1 and 2, which determine if the past values of a variable do not Granger cause the current value of another variable. The p-value for lag 1 of CO2 emission causing GDP (0.006408921) is less than 0.05 significance level, concluding that the past CO2 emission Granger caused GDP. There is evidence that the past level of CO2 emission has a statistically significant influence on current GDP due to factors like policy changes implemented in response to high CO2 emissions. The p-value for lag 1 of CO2 emissions causing the Forest Area (0.0035851) is also less than a common significant level (0.05), inferring that past CO2 emissions caused the Forest Area. Potentially, high CO2 emissions led to policies or behaviors that affect forest cover.

Table 11: Granger Causality Test Results.

Lag Order	CO2_emission to GDP	CO2_emission to Forest_area	GDP to CO2	GDP to Forest_area	Forest_area to CO2_emission	Forest_area to GDP
1	0.681254	0.0035851	0.006408921	0.23533	1.579e-05	0.00648512
2	0.504451	0.0923536	0.0110298	0.0536422	0.00012017	0.0065086

The reported p-values for GDP Granger causing CO2 emissions (0.681254 for lag 1 and 0.504451 for lag 2) are greater than a standard significance level (0.05), signifying no evidence that past GDP Granger causes current CO2 emission at these lags. For the remaining relationship (Forest Area Granger causing GDP and CO2, GDP Granger causing Forest Area) similarly. For instance, the very low p-value (1.579e-05) for Forest Area Granger causing CO2 emission at lag 1 suggests a statistically significant causal effect from past Forest Area to current CO2 emissions.

The Toda-Yamamoto causality test results in Table 12 claim that the p-value for both lag orders 1 and 2 are less than the typical significance level of 0.05, signifying evidence of Ganger causality between variables at both lag orders. The Toda-Yamamoto Causality Test is a better approach for measuring causality in an ARDL model with CO2 emissions as the endogenous variable and forest cover and GDP as exogenous variables. Further, the test is a suitable alternative to the Granger Causality Test as it allows for additional lagged variables and testing for causality in a more general framework.

Table 12: Toda-Yamamoto Causality Test.

Lag Order	Toda-Yamamoto p-value
1	0.008228
2	0.035538

Table 13 shows the results of the Ljung-Box test for autocorrelation, known as serial correlation up to lag 10 in the error terms. All p-values from Lag_1 to Lag_10 are greater than 0.05, indicating no autocorrelation with the tested lags, suggesting that the errors are independent and do not violate model assumptions types of the error cases.

Table 13: Autocorrelation Test (Ljung-Box Test).

	Q-statistics	p-value
Lag_1	0.0215824	0.88357
Lag_2	0.0239325	0.988787
Lag_3	0.0478695	0.994512
Lag_4	0.0691591	0.998668
Lag_5	0.0699545	0.999815
Lag_6	0.0732089	0.999974
Lag_7	0.0941073	0.999996
Lag_8	0.132683	0.999999
Lag_9	0.132683	0.999999
Lag_10	0.133085	1.000000

Table 14 presents the result of two diagnostic tests used to measure potential issues in the regression model. The Lagrange Multiplier Statsitics (LM) and LM p-value (0.187069 and 0.66541) statistics are not directly interpretable. However, the high p-value (0.66541) indicates a failure to reject the null hypothesis of homoscedasticity. Although the F-statistics and F-statistics p-values (0.0451044 and 0.83149) are reported, they are not used for interpretation in White's test. The high p-value (0.83149) is consistent with the LM p-value, indicating no evidence of homoscedasticity.

Table 14: Lagrange Multiplier Statistics (LM) result.

	Lagrange Multiplier Statistic	LM p-value	F-statistic	p-value
Heteroscedasticity Test (White's Test)	0.187069	0.66541	0.0451044	0.83149
Serial Correlation Test (Breusch-Godfrey Test)	0.0002316	0.98948	0.0002316	0.98948

The Lagrange Multiplier Statistics (LM) and the LM p-value (0.0002361 and 0.98948) are similar to the heteroscedasticity test; the LM statistic is not directly evident in the result. A very high p-value (0.98948) indicates no presence of serial correlation. As with White's test, the F-statistic depicts no significant correlation. Based on the p-values reported for both tests, there is no statistical evidence of heterogeneity or serial correlation in the model's error terms. It shows that assumptions about the error terms are handled.

Depicted in Table 15 is the negative coefficient of Forest_area_lag1 (-0.0104), and its marginal significance (p-value = 0.048) portrays a possible long-run negative effect of deforestation on CO2 emissions consistent with the understanding that forests serve as vital carbon sinks, absorbing and storing carbon dioxide from the atmosphere through the process of photosynthesis. The depletion of forest area through deforestation reduces ecosystems' capacity to sequester carbon, resulting in increased CO2 emissions over time (Lorenz, 2010). For the Philippines, this observation focuses on forest conservation (Sheeran, 2006) and sustainable land management (Pulhin et al., 2007) practices in alleviating climate change and reducing greenhouse gas emissions. Initially, economic development causes deforestation as land is claimed for resources; the negative long-term effect on CO2 emissions requires policies and initiatives to preserve and restore forest ecosystems. In the long run, the critical role of forests in trapping carbon underscores the importance of integrating environmental conservation into economic development strategies to attain long-term sustainability.

The displayed positive and statistically significant coefficient of CO2_emission_lag1 (1.5499) in Table 5 conveys that in the short-run, a positive relationship exists between economic growth (GDP_lag1) CO2 emissions aligning with the initial phase of the EKC hypothesis, which infers that as the Philippine economy initially develop and industrialize, environmental deterioration, including CO2 emission tend to increase. During the early 1990s in the Philippines, factors such as increased industrial production, urbanization, and energy consumption lead to higher pollution levels (Raihan, 2023). The positive coefficient conveys that as GDP increases in the previous period, CO2 emission is also likely to increase in the current period, showing the emission-intensive nature of economic activities during this phase. It is important to note that the short-term positive relationship between GDP and CO2 emission in the Philippines aligns with the initial phase of the EKC.

The presented negative and statistically significant coefficient of CO2_emission_lag2 (-0.5591) is compelling evidence for a long-run negative relationship between economic growth and CO2 emissions in the Philippines, supporting the latter phase of the EKC hypothesis proposing that as economies mature, they reach higher income levels and environmental deterioration declines. At this phase, the population prioritizes environmental quality over rapid economic expansion and implements stringent environmental regulations and policies. In the case of the Philippines, these laws and regulations were passed in the later part of the 1990s and early 2000s (Environmental Compliance Assistance Center, 2021). The negative coefficient implies that as the Philippines' GDP increases in the previous two periods, CO2 emissions tend to decrease in the current period, reflecting the adoption of green technologies (Juan, 2020), improved energy efficiencies (Hu & Kao, 2007), and shift towards less carbon-intensive production processes (Cayamanda et al., 2017) as Philippine economy evolve. Further, it underlines the effectiveness of environmental policies and regulations in reducing environmental pollution and promoting sustainable development. Hence, the negative relationship between GDP and CO2 emissions in the long run confirms the concept that economic growth can be decoupled from environmental degradation, eventually leading to a cleaner and more sustainable future.

The highly negative and statistically significant coefficient of GDP_lag1 (-0.0004) points to a pronounced negative short-run impact of economic growth on the forest area. These findings resonate with the early stages of the EKC hypothesis, where rapid economic growth is often accompanied by extensive resource exploitation and land conversion, resulting in deforestation and loss of forest cover (Caravaggio, 2020). As the Philippine economy underwent initial industrialization and urbanization, demand for natural resources such as timber, agricultural land, urban expansion, and industrial estate to support growing economic activities (López & Galinato, 2005). The negative coefficient indicates that as GDP increases in the previous period, forest area tends to decrease in the current period, reflecting the pressure on natural ecosystems from economic expansion (Caravaggio, 2020). However, based on the EKC trajectory, the negative short-run impact of economic growth on the forests is minimized over time. As economies shift towards a more advanced level of development (Pablo-Romero et al., 2023), environmental awareness increases (Chen et al.,2019), and policies (Toledo et al., 2022) are implemented to promote sustainable forest management practices, conservation efforts, and reforestation initiatives. Thus, while there is a negative relationship between GDP and forest area in the short run, despite the initial phase of resource exploitation and land conversion, long-term strategies focused on environmental conservation and sustainable development help reverse this trend and advance ecosystem resilience.

5. Conclusion and Recommendation

The ARDL (2,1) model's analysis of the relationship between GDP, forest area cover, and CO2 emissions furnish essential insights into the interactions between economic growth and environmental sustainability. The statistically significant positive coefficient of CO2_emissions_lag1 claims that the short-run economic growth is associated with increased CO2 emission, inferring the early stage of the EKC, were urbanization and industrialization result in higher pollution. Contrary, the statistically significant negative coefficient of CO2_emission lag2 conveys that in the long run, economic growth contributes to the reduction in CO2 emissions, supporting the later stage of the EKC, where mature economies impose effective environmental regulations and adopt green technologies, thereby reducing pollution.

Also, the highly negative and significant coefficient of GDP_lag1 displays a strong short-run negative impact of economic growth on the forest area, underlining the increased resource consumption and deforestation distinctive of early development stages. However, the negative coefficient of Forest_area_lag1, although slightly significant, suggests that deforestation poses a negative long-term impact on CO2 emissions, focusing on the vital role of forests in carbon sequestration. These findings commonly describe the complex interaction between economic development, environmental degradation, and the importance of considerable practices.

Based on the result of this study, several recommendations for policymakers and stakeholders aim to balance economic growth with environmental sustainability. Given the long-run analysis supporting the EKC hypothesis, policymakers should implement stringent environmental regulations to promote a more sustainable path of economic growth, explicitly setting emission reduction targets and promoting green technologies. With the significant negative effect of deforestation on CO2 emissions, it is critical to implement sustainable forest management practices. Policies should advance conservation efforts, afforestation, and reforestation to increase the carbon sequestration capacity of forests to alleviate the adverse effects of deforestation.

Transitioning from the initial stage of economic growth, considering the high pollution to a more sustainable phase, prioritizing the technologies on clean and renewable energy, which includes offering incentives for adopting and developing green technologies in industries and urban areas. Improving awareness regarding the importance of sustainable development and environmental conservation among individuals, communities, and businesses is vital. Outreach programs and education encourage sustainable practices and raise a culture of environmental stewardship. Further, continuous evaluation and monitoring of environmental policies are useful to evaluate their effectiveness and suggest data-driven adjustments.

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