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Determinants of Environmental Sustainability in Nigeria: A New Insight from Load Capacity Factor

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Abstract

The study examines the determinants of environmental sustainability in Nigeria, with a focus on the Load Capacity Factor (LCF) within a time frame of 52 years (1970-2022). The study utilizes time-series data sourced from the Global Footprint Network, International Energy Agency and World Bank. The data were analyzed using the Multivariate Vector Error Correction Model (VECM) approach to capture both the short-run dynamics and long-run equilibrium relationships among the variables. The study finds that the series are integrated of order I(1), indicating that the variables are non-stationary at level but stationary after first differencing. The Johansen cointegration test reveals long-run cointegration relationships among the variables. The Vector Error Correction Model (VECM) analysis demonstrates that in the short run, the error correction term indicates that about 31.96% of the disequilibrium from the previous period's shock is corrected in the current period, showing a moderate speed of adjustment towards long-run equilibrium. GDP and urbanization negatively impact LCF, while natural resource rent negatively affects LCF and renewable energy consumption positively influences it. The long-run analysis shows that GDP, squared GDP, urbanization, and natural resource rent have a significant negative effect on LCF, whereas renewable energy consumption has a significant positive effect. Granger causality tests show that all independent variables Granger-cause LCF, suggesting uni-directional relationships. The diagnostic tests for the Vector Error Correction Model (VECM) confirm that the model is statistically sound and reliable. The Jarque-Bera test shows that the residuals are normally distributed, while the LM test indicates no serial correlation up to lag 2. Additionally, the heteroskedasticity test confirms that the residuals are homoscedastic. These results validate the model's assumptions of white noise residuals and support its overall adequacy for analysis. Recommendations include focusing on sustainable urban planning, effective resource management, and increasing renewable energy adoption.

Keywords: Load Capacity Factor, Ecological Footprint, Biocapacity, Gross Domestic Product
JEL Classification:

Contribution to/Originality Knowledge

1.0 Introduction

Environmental sustainability has become a major global concern as nations strive to balance economic development with ecological preservation. The load capacity factor (LCF), defined as the ratio of biocapacity to ecological footprint, serves as a vital measure of a region's environmental sustainability, reflecting its ability to support human activities within ecological limits (Yıldırım, Destek, & Manga, 2024; Behera, 2024). Rapid urbanization, industrialization, and reliance on non-renewable energy sources have exacerbated environmental degradation worldwide. In developing countries like Nigeria, these challenges are particularly acute, as urbanization often outpaces infrastructure development, leading to overburdened systems, pollution, and loss of biodiversity (Zahoor et al., 2020). Nigeria faces unique environmental challenges due to its rapid urbanization and heavy dependence on natural resource rents, particularly from the oil and gas sector. Cities like Lagos, Kano, and Abuja are expanding at unprecedented rates, with Lagos projected to become one of the world's largest megacities by 2050, housing over 30 million people (Pata & Isik, 2021). This urban sprawl has led to deforestation, biodiversity loss, and increased pollution, significantly expanding the ecological footprint. Furthermore, Nigeria's heavy dependence on the oil and gas sector which contributes approximately 10% to the nation's GDP and generates over 90% of its export earnings has led to significant environmental degradation. This includes widespread oil spills, persistent gas flaring, and severe water pollution (Afshan, Ozturk, & Yaqoob, 2022). These activities have diminished Nigeria's biocapacity, pushing the LCF lower and threatening long-term sustainability.

The energy landscape in Nigeria further complicates environmental sustainability efforts. Despite its vast potential for renewable energy, the country remains heavily reliant on fossil fuels, with renewable sources contributing less than 20% to the energy mix (Khan et al., 2022). This reliance exacerbates environmental degradation and limits the potential for reducing the ecological footprint. Transitioning to renewable energy is crucial for improving Nigeria's LCF by reducing greenhouse gas emissions and promoting sustainable resource use. However, empirical research on the combined impact of urbanization, natural resource rents, and renewable energy consumption on Nigeria's LCF remains limited, creating a significant gap in the literature. Statistics highlight the severity of Nigeria's environmental challenges. The urban population has surged from 35% in 1990 to 51% in 2021, while the ecological footprint per capita has risen from 1.1 global hectares in 2000 to 1.5 in 2020. Concurrently, biocapacity per capita has declined from 1.8 to 1.3 global hectares over the same period (World Bank, 2021). Oil spills, averaging 500 annually from 2010 to 2020, have caused extensive environmental damage, particularly in the Niger Delta (NNPC, 2020). These trends underscore the urgent need for evidence-based policies to address the interplay between economic growth and environmental sustainability.

Despite the critical importance of environmental sustainability, there remains a notable gap in empirical research that simultaneously investigates the effects of urbanization, natural resource rents, and renewable energy consumption on Nigeria’s Load Capacity Factor (LCF). Most existing studies tend to examine these variables in isolation focusing on issues like pollution or resource depletion without integrating them to assess their combined impact on environmental outcomes. Furthermore, many of these studies have been conducted in contexts outside Nigeria, such as those by Sun et al., (2023), Awosusi et al., (2023), Caglar et al., (2023), Ozkan, Destek, and Aydin (2024), Alola, Özkan, and Usman (2023), and Ulussever, Kartal, and Pata (2024). As a result, the long-run relationships and causal dynamics among these critical variables remain insufficiently explored within the Nigerian context an understanding that is essential for effective policy formulation.

This study addresses that gap by investigating the determinants of environmental sustainability in Nigeria, with a particular focus on how urbanization, natural resource rents, and renewable energy consumption influence the country's LCF. It aims to provide a comprehensive analysis by examining both the long-run relationships and causal links among these variables. Through this approach, the study offers a robust empirical basis for policymaking geared toward sustainable development. The findings will significantly contribute to the discourse on environmental sustainability in Nigeria, offering evidence-based recommendations for balancing economic growth with ecological preservation. Moreover, by identifying key drivers of environmental sustainability, the study supports progress toward achieving Sustainable Development Goals (SDGs) 11 (Sustainable Cities and Communities) and 13 (Climate Action). The research not only enhances academic understanding but also offers practical insights for policymakers and stakeholders. Its innovative use of the Load Capacity Factor as a sustainability metric provides a fresh perspective on evaluating environmental performance. Additionally, raising awareness about the environmental consequences of urban expansion and resource exploitation, as well as the advantages of renewable energy adoption, can motivate both public and private sectors to pursue more sustainable practices.

2.0 Literature Review

2.1 Conceptual Review

Environmental sustainability has become a pressing concern globally, particularly in developing economies such as Nigeria. It refers to the ability of the environment to support ecological processes and human well-being over the long term. A vital metric for assessing environmental sustainability is the Load Capacity Factor (LCF) defined as the ratio of a region's biocapacity to its ecological footprint. An LCF greater than one indicates ecological surplus, while a value below one suggests unsustainable resource use. This study examines the determinants of environmental sustainability in Nigeria, focusing on macroeconomic and environmental indicators such as GDP per capita, squared GDP per capita, urbanization, natural resource rents, and renewable energy consumption.

GDP per Capita (LGDP) is used to measure the level of economic development. At the early stages of growth, economic activities often lead to increased resource consumption and pollution, thereby lowering environmental quality and LCF. Squared GDP per Capita ($LGDP^2$) is introduced to capture the non-linear effects of economic growth on the environment. A negative coefficient on $LGDP^2$ supports the Environmental Kuznets Curve (EKC) hypothesis, suggesting that after a threshold level of income, further growth enhances environmental sustainability. Urbanization is a dual-edged phenomenon. In Nigeria, rapid urbanization has resulted in deforestation, biodiversity loss, increased emissions, and ineffective waste management, all of which contribute to higher ecological footprints and lower LCF. However, when urban growth is well-managed, it can promote efficient resource use and improved environmental practices (Uzlu, 2024).

Natural resource rents, especially from the oil and gas sector, significantly contribute to Nigeria's GDP. However, the extraction and exploitation of these resources often result in environmental degradation, including oil spills, gas flaring, and loss of ecosystems. Renewable energy consumption is widely considered a crucial factor for enhancing environmental sustainability. The shift from fossil fuels to clean energy sources such as solar, wind, and hydropower can reduce carbon emissions and environmental degradation, thereby improving the LCF (Adewole & Osabuohien, 2021).

2.2 Theoretical Review

The main theoretical framework underpinning this study is the Environmental Kuznets Curve (EKC) hypothesis. Originally formulated by Grossman and Krueger (1991, 1995) and expanded by Panayotou (1993), the EKC posits an inverted U-shaped relationship between environmental degradation and economic development. In the early stages of economic growth, degradation rises due to increased industrial activities and weak regulatory frameworks. However, as income increases, investments in cleaner technologies, environmental awareness, and stronger institutions lead to environmental improvements.

Several mechanisms support the Environmental Kuznets Curve (EKC) hypothesis, including structural economic transformation from agriculture and manufacturing to services, which typically reduces pollution; technological innovation that enhances production efficiency and environmental friendliness (Andreoni & Levinson, 2001); and increased environmental awareness and regulation that often accompany higher income levels (Dasgupta et al., 2002). However, the EKC has faced considerable criticism. Methodologically, its validity is highly sensitive to variable selection, model specification, and estimation techniques (Dinda, 2004). Critics argue that it fosters false optimism by assuming economic growth alone will resolve environmental issues, potentially weakening the case for urgent environmental policies (Arrow et al., 1995). Additionally, equity concerns arise, as environmental degradation may disproportionately impact poorer populations even as average incomes rise (Stern, 2004). Finally, the EKC primarily addresses local pollutants and may fail to adequately reflect broader global environmental challenges such as climate change (Stern et al., 1996).

Nevertheless, the EKC remains relevant for analyzing the interplay between economic growth and environmental sustainability, particularly in Nigeria where economic development continues to depend on extractive industries and urban expansion. When assessed using LCF, the EKC provides a nuanced understanding of how income dynamics affect the country's environmental limits.

2.3 Empirical Review

A growing body of empirical literature explores the interactions between economic growth, urbanization, natural resources, renewable energy, and environmental sustainability using various analytical approaches such as ARDL models, quantile regression, and dynamic simulations.

Several studies underscore the positive role of renewable energy in enhancing environmental quality. Khan et al., (2022) and Ahmed et al., (2020) found that increased renewable energy consumption reduces ecological footprints. Similarly, Awosusi et al., (2023) and Sun et al., (2023) confirmed that renewable energy usage positively impacts the LCF in Japan and Malaysia, respectively. However, Agila et al., (2022) and Ding et al., (2023) argue that the effectiveness of renewable energy policies may vary across countries and income groups, highlighting the need for localized approaches. Studies such as Guloglu and Pata (2023) and Afshan et al., (2022) support the EKC hypothesis, finding an inverted U-shaped relationship between income and environmental degradation. In contrast, Alola et al., (2023) and Pata and Isik (2021) challenge this assertion, showing that the Load Capacity Curve (LCC) hypothesis does not hold in countries like India and China, where economic expansion continues to deteriorate environmental quality.

The exploitation of natural resources is another frequently examined variable. Ahmed et al., (2020) and Caglar et al., (2023) report that resource abundance is linked to higher ecological footprints, reflecting unsustainable extraction practices. Likewise, Yang et al., (2023) and Ozkan et al., (2024) document that natural resource rents negatively influence environmental sustainability. However, Ahmed et al., (2020) highlight the mitigating effect of human capital development, suggesting that education and skilled labor can help manage environmental outcomes more effectively. Urbanization trends are similarly found to impact environmental sustainability. The rapid and often poorly regulated urban expansion in many developing countries, including Nigeria, correlates with increased pollution and declining LCF. Yet, several authors emphasize that with proper planning, urban areas can become centers of green infrastructure and sustainable practices.

Akinyemi and Alege (2022) confirm the Environmental Kuznets Curve, showing economic growth initially harms but later improves environmental quality, with renewable energy reducing pollution and urbanization worsening it. Adewole and Osabuohien (2021) highlight that natural resource exploitation drives environmental degradation, emphasizing the need for better governance and economic diversification. Giwa et al., (2020) demonstrate that renewable energy consumption significantly lowers CO_2 emissions, contrasting with fossil fuels and economic growth that increase pollution, advocating for policies promoting clean energy adoption. The literature reveals complex and often context-dependent relationships between economic, demographic, and energy variables and environmental sustainability. While the EKC hypothesis offers a theoretical framework for examining these dynamics, empirical findings remain mixed. Factors such as renewable energy consumption, urbanization, and resource dependency play crucial roles in shaping environmental outcomes. For Nigeria, addressing environmental sustainability demands policies that promote economic diversification, energy transition, and sustainable urban development, supported by robust institutional frameworks and data-driven decision-making.

The literature indicates significant relationships between environmental sustainability and factors like economic growth, urbanization, renewable energy, and natural resources. However, few studies provide an integrated analysis of these variables using LCF in the Nigerian context. There is also limited exploration of long-run relationships and causality, which are essential for effective policy formulation. This study addresses these gaps by providing empirical evidence from Nigeria using recent data. Exploring both long-run and short-run dynamics between urbanization, resource rents, renewable energy consumption, and LCF. Enhancing the literature with policy-relevant insights that align with SDG 11 (Sustainable Cities) and SDG 13 (Climate Action).

3.0 Methodology

3.1 Theoretical Framework

The theoretical foundation of this study rests on the Environmental Kuznets Curve (EKC). It addresses the pressing issue of environmental degradation threatening the sustainability and prosperity of economies at various development stages (Grossman & Krueger, 1991. Research examining the EKC hypothesis shares common traits in terms of data and methods. In essence, despite employing various analysis methods and techniques for the EKC, nearly all of them adhere to a similar model structure. The typical theoretical representation of the EKC model is often outlined as follows (Stern, 2004):

$$Y_t = \alpha_t + \beta_1 X_t + \beta_2 X_t^2 + ... + \beta_4 Z_t + \varepsilon_t \quad (1)$$

Where 'y' denotes environmental metrics, 'α' stands for the constant, 'x,' and 'x2' symbolize income levels and squared income levels, respectively. 'βk' represents the estimated coefficients in the regression, 'z' accounts for other relevant model indicators, 't' denotes time (years), and 'ε' refers to random noise.

3.2 Model Specification

Following the standard EKC hypothesis and building upon the work of Pata and Isik (2021), Alola et al., (2023); Yıldırım et al., (2024) with some modifications. The model specification is given as:

$$LCF = f\left(GDP, GDP2, URB, NRR, REC\right) \quad (2)$$

Putting the above equation into an econometric model

$$LCF = \beta_0 + \beta_1 GDP_t + \beta_2 GDP_t^2 + \beta_3 URB_t + \beta_4 NRR_t + \beta_5 REC_t + \mu \quad (3)$$

Where

B_0, β_1 - β_5 = Parameters, μ = Stochastic or error term, LCF= Load Capacity Factor (Ecological Footprint/Biocapacity), GDP= Gross Domestic Product per Capita, GDP2 = Squared Gross Domestic Product per Capita, URB = Urbanization, NRR =Natural Resource Rent, REC = Renewable Energy Consumption.

All variables were transformed into their natural logarithms, following the methodology of Khan et al., (2020) and Shen and Yue (2023). To estimate the model, the Vector Error Correction Model (VECM) was employed. According to Engle and Granger (1987), VECM captures both short-run dynamics and long-run equilibrium relationships when the variables are cointegrated of order 1(1). The specific VECM specification used in this study is presented in equation 4.

$$\Delta(\ln LCF)_t = \alpha_0 + \alpha \ln LCF \phi_{t-1} \sum_{i=1}^{g_1} \alpha_{1i} \Delta(\ln LCF)_{t-1}$$
$$+ \sum_{i=1}^{h_1} \rho_{1i} \Delta(\ln GDP)_{t-1} + \sum_{i=1}^{r_1} \lambda_{1i} \Delta(2 * \ln GDP)_{t-1} + \sum_{i=1}^{d_1} \eta_{1i} \Delta(\ln URB)_{t-1} \quad (4)$$
$$+ \sum_{i=1}^{v_1} \gamma_{1i} \Delta(\ln NRR)_{t-1} + \sum_{i=1}^{s_1} \theta_{1i} \Delta(\ln REC)_{t-1} + \varepsilon_{1t}$$

Where: α_0 = Constant parameter, Δ = Denote the different operators, $\sum$=Vector of coefficient variables in the model, Y_t =Dependent variable at time t, $(\rho, \lambda, \eta, \gamma, \theta)$ = Are slop coefficient of independent variable

3.3 Sample Size

This research covers a period of 52 years from 1970 to 2022. The chosen period is justified by the standard requirement in time series analysis, which recommends a minimum of thirty (30) observations to ensure reliable and robust estimation results. This indicates the sample size of 52 which is enough to be considered as valid sample size as it was suggested by the Central limit theory (Gujarati, 2007). The chosen scope of this study, spanning from 1970 to 2022, is essential to capture the long-term trends and patterns in Nigeria's urbanization, natural resource exploitation, and renewable energy adoption. This period encompasses significant historical, economic, and environmental changes, including the oil boom of the 1970s, economic liberalization in the 1980s and 1990s, and recent initiatives toward renewable energy and environmental conservation. By covering these decades, the study ensures sufficient data availability and reliability, allowing for a comprehensive analysis of how these factors have influenced the load capacity factor over time.

3.4 Type and Sources of Data

This study relies primarily on secondary sources, utilizing time series data. Specifically, data on the Load Capacity Factor (calculated as Biocapacity divided by Ecological footprint) were obtained from the Global Footprint Network (GFN). Data on Gross Domestic Product per Capita (GDP), Natural Resource Rent, and Urbanization was sourced from the World Development Indicators (WDI), while data on Renewable Energy Consumption were collected from the International Energy Agency (IEA).

3.5 Variables Measurement

The Load Capacity Factor (LCF) serves as a key indicator of environmental sustainability, defined as the ratio of a country's biocapacity (its ability to regenerate renewable resources and absorb waste) to its ecological footprint (the demand exerted on these resources by human activities). Measured in global hectares (gha), a higher LCF indicates more sustainable resource use where biocapacity meets or surpasses ecological footprint as adopted by Pata and Isik (2021), Alola, Özkan, and Usman (2023), and Yıldırım, Destek, and Manga (2024).

Gross Domestic Product (GDP) per capita, expressed in constant 2015 US dollars, represents the average economic output per person and serves as a proxy for income level and living standards. In this study, it is used to assess the economic dimension of environmental sustainability.

The squared GDP per capita (GDP^2) is included to capture potential non-linear effects between economic growth and environmental outcomes, consistent with the Environmental Kuznets Curve (EKC) hypothesis.

Urbanization is measured as the percentage of the total population residing in urban areas. It reflects demographic shifts and infrastructure expansion that can significantly influence environmental outcomes, as demonstrated in studies by Nathaniel (2020) and Talib et al., (2022).

Natural Resource Rent, calculated as a percentage of GDP, reflects the net gains from the extraction of natural resources such as oil, minerals, and timber. Its impact on sustainability depends on how these rents are managed, following the approach of Ahmad et al., (2020) and Radmehr et al., (2022).

Lastly, Renewable Energy Consumption measured in billions of kilowatt-hours per capita or gigajoules, and expressed as a share of total energy consumption represents the use of clean energy sources like solar, wind, and hydropower. It plays a vital role in reducing environmental degradation, as emphasized by Sampene et al., (2022), Adebayo et al., (2022), Pata et al., (2021), and Zafar et al., (2019).

3.6 Techniques of Estimation

3.6.1 Unit Root Test for Stationarity

Stationarity is a fundamental requirement for reliable forecasting and meaningful econometric inference. Macroeconomic time series data are often non-stationary at level, necessitating transformation through differencing to achieve stationarity. To test for stationarity, this study employs two widely recognized unit root tests: the Augmented Dickey-Fuller (ADF) test and the Phillips-Perron (PP) test. Conducting unit root tests is crucial to avoid spurious regression results, where high R-squared values and statistically significant t-statistics may be misleading and lack true economic interpretation (Phillips & Perron, 1988; Toda & Yamamoto, 1995). These tests help determine the order of integration of each variable. A time series is said to be integrated of order zero, I(0), if it is stationary at level, meaning no unit root is present. If a variable attains stationarity only after first differencing, it is considered integrated of order one, I(1) (Dickey & Fuller, 1979; Dickey & Fuller, 1981). Identifying the integration order of variables is a prerequisite for conducting cointegration analysis, ensuring the appropriate transformation of data for robust econometric modeling. The regression model used for unit root testing is specified as follows:

$$\Delta Y_t = \beta_1 + \beta_{2t} + \beta y_{t-1} + \alpha_i \sum_{i=1}^{m} \Delta y_{t-1} + \varepsilon_t \tag{5}$$

Where ΔY_t=difference between variable and its own lag, β1=constant trend, β2=is the parameter of time trend, δ = unit root, y(t-1) = the immediate previous observation

3.6.2 Optimum lag Test

Prior to conducting the cointegration test, it is crucial to identify the optimal lag length to be included in the model, as emphasized by Gorden (1995). Selecting the appropriate lag ensures that the dynamic behavior of the variables is properly captured. Several statistical criteria are commonly employed for this purpose, including the Akaike Information Criterion (AIC), Final Prediction Error (FPE), Schwarz Bayesian Information Criterion (SBIC), and Hannan-Quinn Information Criterion (HQIC). The optimal lag length is determined based on the value most frequently suggested across these criteria. Establishing the correct lag structure is a necessary step to enhance the accuracy and reliability of the subsequent cointegration analysis.

3.6.3 Cointegration Test

Given that most macroeconomic variables are non-stationary at level but become stationary after first differencing, it is important to assess whether a stable long-run equilibrium relationship exists among them. This is the essence of cointegration analysis. Once the appropriate lag length is determined, the Johansen cointegration test is applied to ascertain the existence of long-run relationships. This test, developed by Johansen and Juselius, utilizes two key statistics: the Trace statistic and the Maximum Eigenvalue statistic. These statistics are compared against their respective 5% critical values to determine the number of cointegrating vectors. The null hypothesis of no cointegration is rejected if either statistic exceeds the critical value, indicating the presence of a cointegrating relationship. If cointegration is confirmed, a Vector Error Correction Model (VECM) is employed to capture both the long-run equilibrium and short-run dynamics. In the absence of cointegration, a Vector Autoregressive (VAR) model in first differences is used instead (Johansen, 1988). This procedure ensures the robustness and validity of the model in analyzing the interrelationships among the variables.

3.6.4 Vector Error Correction Model

In its basic form, a Vector Autoregression (VAR) model consists of a set of K endogenous variables, represented as:

$$Y_t = \left(y_{(1t,)} \ldots, y_{(2t)}, \ldots, y_{kt} \right) \tag{6}$$

For k = 1…p

The VAR (p)-process is then defined as:

$$y_t = A_1 y_{(t-1)} + \cdots + A_P Y_{t-p} + u_t \tag{7}$$

A_i represent the (K×K) coefficient matrices for I = 1… p and u_t, t denote a k-dimensional white noise process such that i = 1… p and u_t and the covariance matrix E (u_t, u_t^T)=∑_u is time-invariant and positive definite. A key property of a VAR(p) process is stability, which implies that the process generates stationary time series with constant (time-invariant) means, variances, and covariances provided that appropriate initial values are specified. We now reconsider the VAR model specified in Equation 1 under this stability condition.

$$y_t = A_1 y_{t-1} + \cdots + A_P Y_{t-p} + u_t \tag{8}$$

The following Vector Error Correction (VEC) model specifications are applicable and can be estimated using the relevant built-in functions.

$$\Delta yt = \alpha\beta y_{t-1} + \Gamma_1 \Delta\, y_{t-1} + \ldots + \Gamma_{1+p-1} + \mu_t \tag{9}$$

$$\Gamma_1 = -\left(I - A_1 - \ldots - A_1\right),\ i = 1,\ldots,p-1$$
$$\pi = \alpha\beta^T = -\left(1 - A_1 - \ldots - A_p\right)$$

The Γ_i matrices in the Vector Error Correction Model (VECM) represent the cumulative long-run effects, which is why this version of the model is referred to as the “long-run” specification. An alternative and commonly used representation of the VECM is given by:

$$\begin{aligned} \Delta y_t &= \alpha\beta y_{t-1} + \Gamma_1 \Delta y_{t-1} + \ldots + \Gamma_{1+p-1} + \mu_t \\ \Gamma_1 &= -\left(A_{1+1} + \ldots + A_p\right), \quad i = 1,\ldots,p-1 \end{aligned} \tag{10}$$

In this formulation, the matrix π is defined as π=αβ^Tis, consistent with the previous specification. However, the Γi matrices in this form capture the short-run or transitory dynamics of the system. When cointegration is present, the matrix π\piπ has reduced rank rrr, indicating the number of long-run equilibrium relationships among the variables in yt. Here, α is known as the adjustment or loading matrix, and β contains the coefficients of the cointegrating vectors, with both having dimensions rK×r.

3.9.5 VEC Granger Causality Block Exogeneity Wald Test

The Granger Causality Block Exogeneity Wald test is employed to determine the direction of causality among the variables. This approach offers advantages over the traditional Pairwise Granger Causality test, as it does not require prior testing for cointegration, thereby eliminating biases that may arise from unit root and cointegration procedures. Moreover, the Block Exogeneity Wald test is versatile it can be applied irrespective of the integration order of the variables, whether they are I(0), I(1), or I(2), and whether or not they are cointegrated (Granger, 1969; Granger, 1988). This robustness makes it particularly suitable for complex time series data. The null hypothesis of no causality is rejected when the computed test statistic exceeds the critical value, indicating the presence of causality from one variable to another. The test statistic used in this procedure is as follows:

$$F = {}^{(SSE_{reduced} - SSE_{full}) / K_{full} - K_{reduced}} \Big/ {}_{SSE_{full}} / n - K_{full}^{-1}) \tag{11}$$

And the critical value used as

$$F \propto (k_{full} - k_{reduced})(n - k_{full}^{-1}) \quad (12)$$

3.7 Diagnostic Test

The diagnostic tests conducted for the estimated model included the Breusch-Godfrey LM Test for autocorrelation, the Jarque-Bera (JB) Test for normality, and the Breusch-Pagan-Godfrey Test for heteroscedasticity. The Breusch-Godfrey LM Test was chosen over the Durbin-Watson and Durbin's h tests due to its ability to detect higher-order serial correlation and handle lagged dependent variables. The null hypothesis of no autocorrelation is rejected if the p-value of the F-statistic is less than the significance level (α). The Jarque-Bera Test assessed whether the error term was normally distributed, with the null hypothesis stating normality; this hypothesis is rejected if the p-value of the JB statistic is below α. Finally, the Breusch-Pagan-Godfrey Test evaluated heteroscedasticity, where the null hypothesis of constant variance (homoscedasticity) is rejected if the p-values of the F-statistic and observed R^2 are less than 0.05, indicating heteroscedasticity. These tests ensure the model's residuals are free from autocorrelation, normally distributed, and homoscedastic, validating the reliability of the estimated results.

4.0 Presentation of Result and Analysis

4.1 Unit Root Result

Consistent with the study's methodology, unit root tests were carried out using both the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) approaches. These tests are crucial for identifying the time series properties of the data and ensuring the reliability of the results by avoiding spurious regressions. The summary of these test results is presented in the table below. Testing for stationarity or the presence of a unit root is a fundamental prerequisite in time series analysis to ensure that the variables exhibit stable statistical properties over time.

Table 4.1 Result of Unit Root Test

Augmented Dickey Fuller (ADF)			
Variables Series	**Level Value**	**First Difference**	**Order of Integration**
LLCF	-0.462649	-4.414575***	I(1)
LGDP	-0.940825	-3.253717***	I(1)
LGDP2	-0.940825	-3.253717**	I(1)
LURB	-1.829558	4.256042***	I(1)
LNRR	-1.242812	-7.055695***	I(1)
LREC	-2.003341	1.054418***	I(1)

Phillips and Perron's (PP)

Variables Series	**Level Value**	**First Difference**	**Order of Integration**
LLCF	-1.581615	-8.027910***	I(1)
LGDP	-1.108361	5.476139***	I(1)
LGDP2	-1.108361	-5.476139***	I(1)
LURB	-2.578270	4.256042***	I(1)
LNRR	-2.102842	-6.828577***	I(1)

LREC	-1.003341	-4.654189***	I(1)

Note that *** indicate significant at 1% level.

The outcomes of the unit root tests are displayed in Table 4.1, which evaluates the null hypothesis of the presence of a unit root using both the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests. At the level form, the null hypothesis could not be rejected, as the absolute values of the test statistics were less than the corresponding critical values in both tests, indicating that the variables are non-stationary at level. However, after first differencing, all variables became stationary, confirming that they are integrated of order I(1) and statistically significant at the 1% level for both the ADF and PP tests. The optimal lag length for the ADF test was selected based on the Schwarz Information Criterion (SIC), while the PP test's bandwidth was determined automatically using the Newey-West method. All tests were conducted with both a constant and a linear trend included.

4.2 Optimum lag Result

Following the ADF and PP unit root tests, the results confirmed that all series variables are stationary at the first difference, i.e., integrated of order I(1). This satisfies the essential condition for conducting cointegration analysis. As a next step, it is crucial to identify the optimal lag length to be included in the regression model to ensure accurate estimation and capture the underlying dynamics of the variables.

Table 4.2 Optimum lag Result

Lag	LogL	LR	FPE	AIC	SC	HQ
0	17.91200	2.021066	4.042132	3.47567	2.501965	1.860574
1	17.87395	2.027038	4.054076	3.49605	2.647773	1.861278
2	18.34806	2.066028*	4.132055*	3.96549*	3.708233*	1.866235
3	17.52215	1.981012	3.962023	2.898726	0.557318	1.852005*
4	17.91231	1.031066	3.042162	3.125671	2.721975	1.461576

Note that * indicate lag order selected by the criterion

As shown in Table 4.2, the optimal lag order selection was conducted to determine the appropriate number of lags to include in the model before proceeding with the cointegration test. The selection was based on five different information criteria. While four of the criteria recommended a lag length of 2, only the HQ criterion suggested a lag length of 3. Given the majority consensus, the study adopted a lag length of 2 as the optimal choice for the model.

4.3 Johansen Cointegration Test Result

The Johansen cointegration test results are presented in Tables 4.3 and 4.4, which show the outcomes of the Trace Statistic and Maximum Eigenvalue tests, respectively. Both tests are used to determine the number of cointegrating relationships among the variables in the model.

Table 4.3 Johansen Cointegration Rank Result (Trace Statistics)

Hypothesized No. of CE(s)	Eigen Value	Trace Statistics	0.05% Critical Value	Prob.
None *	0.674179	155.7799	94.09652	0.0000
At most 1 *	0.472903	100.8310	59.92315	0.0000
At most 2 *	0.449071	69.45282	46.07986	0.0002
At most 3 *	0.381034	40.24153	27.12843	0.0022
At most 4 *	0.257708	16.73602	14.02697	0.0324
At most 5	0.042605	2.133430	2.841465	0.1441

Note that * donate rejection of hypothesis at 5% significant and Mackinn P-Value accordingly. Trace test indicates 5 cointegrating eqn(s) at the 0.05 level

The Johansen cointegration test, using the Trace statistic, evaluates the null hypothesis that there are r cointegrating relationships against the alternative that there are more than r. The null hypothesis is rejected when the Trace statistic exceeds its critical value at the 5% significance level. In this analysis, the Trace statistic for the null hypothesis of no cointegrating vector (r = 0) is 155.7799, which is substantially higher than the critical value of 94.09652, with a p-value of 0.0000, leading to rejection of the null hypothesis. This pattern of rejection continues through "At most 4," with each Trace statistic surpassing its respective critical value and corresponding p-values below 0.05, indicating the presence of at least five cointegrating vectors. However, for "At most 5," the Trace statistic falls to 2.133430, which is below the critical value of 2.841465, accompanied by a p-value of 0.1441, resulting in a failure to reject the null hypothesis of at most five cointegrating equations.

Table 4.4 Result of Johansen Cointegration Rank Test (Maximum Eigen Value Statistics)

Hypothesized No. of CE(s)	Eigen Value	Max-Eigen Statistic	0.05% Critical Value	Prob.
None *	0.674179	54.94891	41.79732	0.0005
At most 1	0.472903	31.37820	34.38568	0.0065
At most 2 *	0.449071	29.21129	30.24656	0.0307
At most 3 *	0.381034	23.50551	26.78978	0.0227
At most 4 *	0.257708	14.60259	15.96846	0.0442
At most 5	0.042605	2.133430	3.265427	0.1441

Note that * donate rejection of hypothesis at 5% significant and Mackinnon P-Value accordingly. Max-eigenvalue test indicates 2 cointegrating eqn(s) at the 0.05 level

Table 4.4 presents the results of the Johansen cointegration test based on the Maximum Eigenvalue statistic. This test evaluates the null hypothesis of r cointegrating vectors against the alternative hypothesis of r + 1 cointegrating vectors. The null hypothesis is rejected if the Max-Eigen Statistic exceeds the critical value at the 5% significance level.

For the hypothesis of no cointegration (r = 0), the Max-Eigen Statistic is 54.94891, which exceeds the critical value of 41.79732, with a p-value of 0.0005, leading to rejection of the null hypothesis. However, for "At most 1" ($r \leq 1$), the Max-Eigen Statistic is 31.37820, which is slightly below the critical value of 34.38568, resulting in the acceptance of the null hypothesis at the 5% significance level. Moving forward, the test statistics for "At most 2" (29.21129), "At most 3" (23.50551), and "At most 4" (14.60259) all exceed their respective critical values, with corresponding p-values less than 0.05. This indicates rejection of the null hypotheses at these levels. Finally, for "At most 5" (2.133430), the test statistic is less than the critical value (3.265427), leading to acceptance of the null hypothesis. Based on these results, the Maximum Eigenvalue test suggests the presence of two cointegrating equations at the 5% significance level.

Lastly, the Johansen cointegration tests provide evidence of cointegrating relationships among the variables, suggesting that they move together in the long run. This is a critical insight for understanding the system's dynamics and for designing policies that reflect these long-term interdependencies. While the Trace test identified five cointegrating equations, the Maximum Eigenvalue test found two; despite this difference, both tests consistently reject the null hypothesis of no cointegration. This concurrence robustly confirms the existence of long-run relationships between the dependent and independent variables in the model, underscoring the importance of these variables in explaining the system's equilibrium behavior.

4.4 Vector Error Correction Model Result

Table 4.5: Result of Vector Error Correction Model

Variables	**Coefficient**	
	Short-run	**Long-run**
C		-2.341212
LGDP	-3.762208*	-1.082110***
	(2.22108)	(0.155409)
	[-1.69386]	[6.96338]
LGDP2	2.475142	-6.971008**
	(0.54507)	(2.822108)
	[0.70976]	[-2.47014]
LURB	-2.085011*	-2.0996243**
	(1.06748)	(0.827503)
	[- 1.95321]	[-2.53730]
LNRR	-5.348262**	-8.951617***
	(2.41306)	(3.123117)
	[-2.21638]	[-2.86625]
LREC	4.10109*	3.701422***
	(2.14309)	(1.022110)
	[1.91363]	[3.62135]
ECM	-0.319648**	
	(0.11972)	
	[-2.66996]	
R-squared	0.918846	
Adj. R-squared	0.907275	
F-statistic	83.72815***	
Prob(F-statistic)	0.000000	

Note that ***, ** and * indicate level of significant at 1%, 5% and 10% respectively

ECM = size of the error correction terms, Standard errors in ( ) & t-statistics in [ ]

The error correction term (ECM) has a coefficient of -0.319648, significant at the 5% level (t-statistic = -2.66996). This negative and significant coefficient indicates that about 31.96% of the disequilibrium from the previous period's shock is corrected in the current period, showing a moderate speed of adjustment towards long-run equilibrium. The coefficient for GDP in the short run is -3.762208, significant at the 10% level (t-statistic = -1.69386). This indicates that a 1% increase in GDP leads to a 3.762208% decrease in the dependent variable in the short run. Also, the coefficient for the squared GDP is 2.475142, but it is not statistically significant (t-statistic = 0.70976). For urbanization, the coefficient is -2.085011, significant at the 10% level (t-statistic = -1.95321). This implies that a 1% increase in urbanization results in a 2.085011% decrease in the dependent variable in the short run. Additionally, the coefficient for natural resource rent is -5.348262, significant at the 5% level (t-statistic = -2.21638). This suggests that a 1% increase in natural resource rent leads to a 5.348262% decrease in the dependent variable in the short run. The coefficient for renewable energy consumption is 4.10109, significant at the 10% level (t-statistic = 1.91363). This means that a 1% increase in renewable energy consumption results in a 4.10109% increase in the dependent variable in the short run.

In the case of short run result, the VECM results indicated that GDP (LGDP) and urbanization (LURB) negatively impact LCF, aligning with Khan et al., (2022), who found that urbanization worsens the ecological footprint in OECD countries. The negative impact of natural resource rent (LNRR) on LCF in Nigeria is supported by the findings of Afshan, Ozturk, and Yaqoob (2022), who demonstrated similar negative effects in OECD economies. Conversely, renewable energy consumption (LREC) positively affects LCF, resonating with studies such as Behera (2024), which showed renewable energy use mitigates CO2 emissions in OECD countries.

Furthermore, the long-run coefficient for GDP is -1.082110, significant at the 1% level (t-statistic = 6.96338). This indicates that a 1% increase in GDP leads to a 1.082110% decrease in the dependent variable in the long run. Also, the long-run coefficient for squared GDP is -6.971008, significant at the 5% level (t-statistic = -2.47014). This suggests a nonlinear relationship where an increase in GDP2 leads to a significant decrease in the dependent variable. The long-run coefficient for urbanization is -2.0996243, significant at the 5% level (t-statistic = -2.53730). This implies that a 1% increase in urbanization results in a 2.0996243% decrease in the dependent variable in the long run. The long-run coefficient for natural resource rent is -8.951617, significant at the 1% level (t-statistic = -2.86625). This indicates that a 1% increase in natural resource rent leads to an 8.951617% decrease in the dependent variable in the long run. The long-run coefficient for renewable energy consumption is 3.701422, significant at the 1% level (t-statistic = 3.62135). This suggests that a 1% increase in renewable energy consumption results in a 3.701422% increase in the dependent variable in the long run. The constant term in the long-run equation is -2.341212.

In the long run, GDP (LGDP) and its squared term ($LGDP^2$) continued to exhibit a significant negative impact on LCF, suggesting economic growth adversely affects environmental sustainability over time. This is consistent with the Environmental Kuznets Curve (EKC) hypothesis validated by Pata and Isik (2021) in China and Ozkan, Destek, and Aydin (2024) in Germany, where economic growth initially harms environmental quality before improving it at higher income levels. The persistent negative impact of urbanization (LURB) and natural resource rent (LNRR) on LCF in the long run aligns with findings from studies by Ulussever, Kartal, and Pata (2024) in GCC countries and Caglar et al., (2023) in Russia. Also, the significant positive effect of renewable energy consumption (LREC) on LCF in both the short and long run underscores its critical role in enhancing environmental sustainability. This finding is supported by a broad range of literature, including Guloglu, Caglar, and Pata (2023), who emphasized the ecological benefits of renewable energy in OECD countries, and Alola, Özkan, and Usman (2023), who highlighted similar positive impacts in India.

R-squared (R^2) is 0.918846. This statistic indicates that approximately 91.88% of the variability in the dependent variable is explained by the independent variables in the model. This high R-squared value suggests a strong fit of the model to the data. Also, Adjusted R-squared (Adj. R^2) is 0.907275. The Adjusted R-squared value adjusts the R-squared value for the number of predictors in the model, providing a more accurate measure of model fit, especially when multiple predictors are involved. An adjusted R-squared of 90.73% indicates that the model explains a substantial portion of the variability in the dependent variable, accounting for the number of predictors used. The F-statistic is83.72815 (Significant at 1% level). The F-statistic tests the overall significance of the regression model. It assesses whether at least one of the predictors is significantly related to the dependent variable. The high F-statistic value of 83.72815, which is significant at the 1% level, indicates that the independent variables collectively have a statistically significant relationship with the dependent variable.

The short-run and long-run results of the VECM show significant relationships between the dependent variable and the independent variables. In the short run, GDP, urbanization, natural resource rent, and renewable energy consumption significantly impact the dependent variable. The error correction term indicates a moderate speed of adjustment towards equilibrium. In the long run, GDP, urbanization, natural resource rent, and renewable energy consumption also significantly affect the dependent variable, with renewable energy consumption positively impacting it while the others have negative impacts. The results confirm the existence of long-run relationships among the variables in the model. The high R-squared and Adjusted R-squared values suggest that the model explains a substantial portion of the variability in the dependent variable, indicating a strong fit. The significant F-statistic and its corresponding probability value reinforce that the model is statistically significant and that the independent variables, taken together, significantly explain variations in the dependent variable.

4.5 VEC Granger Causality Block Exogeneity Wald Test Result

Table 4.6: Granger Causality/Block Exogeneity Wald Test

Variables	**X^2-statistics of lagged 1st different term [p-value] Variables**					
	$LLCF\phi_{t-1}$	$\Delta(\mathrm{LGDP})_{t-1}$	$\Delta(LGDP2)_{t-1}$	$\Delta(LURB)_{i-1}$	$\Delta(LNRR)_{i-1}$	$\Delta(LREC)_{i-1}$
$\Delta LLCF$	-	1.0841**	0.5034**	0.1940***	2.8569***	2.2247**
$\Delta LGDP$	1.0841	-	2.925385	0.065716	1.152084	0.105779
$\Delta LGDP2$	1.0812	1.081166	-	0.050069	1.295767	0.113253
$\Delta LURB$	1.1427	1.142667	28.23402	-	5.013828	0.370099
$\Delta LNRR$	0.3738	0.373837	11.81265	0.151221	-	0.101960
$\Delta LREC$	0.4933	0.493255	36.02376	339.6882	10.75657	-

Note that ***, **and * indicate 1%, 5% and 10% significant

The test statistic for ΔLGDP is 1.0841, significant at the 5% level. This indicates that GDP growth (ΔLGDP) Granger-causes changes in the Load Capacity Factor (LCF). In other words, past values of GDP growth help predict future values of LCF. Also, the test statistic for ΔLGDP2 is 0.5034, significant at the 5% level. This signifies that the squared term of GDP growth (ΔLGDP2) also Granger-causes changes in LCF. This implies that both linear and nonlinear components of GDP growth are important in predicting LCF. For Urbanization, the test statistic for ΔLURB is 0.1940, significant at the 1% level. This shows that urbanization (ΔLURB) Granger-causes changes in LCF, indicating that past values of urbanization are useful in predicting future values of LCF. Additionally, Natural Resource Rent test statistic is 2.8569, significant at the 1% level. This indicates that natural resource rent (ΔLNRR) Granger-causes changes in LCF, suggesting a strong predictive relationship where past values of natural resource rent can forecast future LCF.

More so, the test statistic for ΔLREC is 2.2247, significant at the 5% level. This shows that renewable energy consumption (ΔLREC) Granger-causes changes in LCF, highlighting the importance of renewable energy consumption in predicting LCF. Lastly, all the tested variables (LGDP, LGDP2, LURB, LNRR, LREC) exhibit a uni-directional causal relationship with LCF. This means each of these variables Granger-causes LCF, but there is no indication of reverse causality from LCF to these variables in the given context. The results suggest that past values of GDP growth, its squared term, urbanization, natural resource rent, and renewable energy consumption can all be used to predict future changes in the Load Capacity Factor.

Furthermore, the VEC Granger Causality Block Exogeneity Wald Test revealed uni-directional causal relationships from all independent variables (LGDP, $LGDP^2$, LURB, LNRR, LREC) to LCF. This finding is in line with Sun et al., (2023), who also found significant predictive power of economic globalization and energy transition variables on ecological sustainability in Malaysia. More also, the findings of this study have important policy implications for Nigeria. The negative impacts of economic growth, urbanization, and natural resource rent on environmental sustainability highlight the need for policies promoting green urbanization and sustainable resource management. The positive influence of renewable energy consumption suggests that expanding renewable energy initiatives could significantly enhance Nigeria's environmental sustainability, a conclusion similarly drawn by Awosusi et al., (2023) for Japan and Zhang (2023) for E7 countries.

4.6 Diagnostic Test

Table 4.7: Diagnostic Test Result for VECM

Tests	Coefficient	P-Value
Jarque-Bera Residual Normality Test	772.0800	0.5031
Serial Correlation LM Test	37.57940	0.3967
Residual Heteroskedasticity Test	485.9280	0.6686

As presented in Table 4.7, the Vector Error Correction Model (VECM) satisfies the key diagnostic tests, confirming the adequacy and reliability of the model. The joint Jarque-Bera statistics indicate that the residuals follow a normal and identically distributed pattern, as evidenced by the insignificant p-value (0.5031). This result implies that the null hypothesis of normality cannot be rejected, thus validating the assumption of normally distributed residuals within the model. Furthermore, the VECM residual serial correlation LM test confirms the absence of autocorrelation up to lag order 2. The corresponding p-value of 0.3967 suggests that we cannot reject the null hypothesis of no serial correlation, indicating that residuals are independently distributed across lags. In addition, the model was subjected to a heteroskedasticity test, and the results further strengthen its reliability. The null hypothesis of homoscedasticity could not be rejected, as indicated by the p-value of 0.6686, demonstrating that the residuals exhibit constant variance over time. Collectively, these diagnostic outcomes support the classical assumptions of white noise residuals and confirm that the specified VECM is both well-fitted and statistically robust for the analysis.

5.0 Conclusion and Recommendations

The study concludes that urbanization, natural resource rents, and renewable energy consumption significantly influence environmental sustainability in Nigeria, as measured by the Load Capacity Factor (LCF). The results indicate that both short-run and long-run dynamics play crucial roles in determining LCF. GDP growth, urbanization, and natural resource rent negatively impact LCF, while renewable energy consumption positively impacts it. These findings highlight the importance of adopting sustainable practices and policies to improve environmental sustainability in Nigeria.

Based on the findings, the following recommendations are made: Policies should be implemented to increase the adoption and consumption of renewable energy sources, as they positively impact environmental sustainability. Urban planning and development strategies should focus on sustainable practices to mitigate the negative impact of urbanization on environmental sustainability. Effective management of natural resources is crucial to reduce their negative impact on environmental sustainability. Policies should aim at optimizing the use of natural resources while minimizing environmental degradation. Diversifying the economy beyond reliance on natural resource rents can help reduce the negative impacts associated with natural resource extraction and use. Lastly, the government should formulate and implement long-term policies aimed at balancing economic growth with environmental sustainability, considering both linear and nonlinear impacts of GDP on LCF.

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