



Dynamic Effect of Environmental Sustainability Determinants on Ecological Footprint in Selected Sub-Saharan African Countries

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Abstract

This study investigates the dynamic effects of environmental sustainability determinants on the ecological footprint in selected Sub-Saharan African countries covering the period of 1970 to 2023. Using the Cross-Sectionally Augmented Autoregressive Distributed Lag (CS-ARDL) model. Cross-sectional dependency and slope homogeneity tests established significant interdependence and heterogeneity of the data. Cross-sectional Augmented Dickey-Fuller (CADF) and Cross-sectional Im, Pesaran, and Shin (CIPS) stationarity test reveals mixture of integration orders. Also, Westerlund (2007) cointegration test confirms long-run relationship among the variables. The CS-ARDL estimation results reveal both long-run and short-run dynamics among the variables. In the short run, economic growth, urbanization, and non-renewable energy consumption have strong positive impacts on EF, while renewable energy has a marginal effect likely due to transitional inefficiencies. The error correction term confirms a moderate adjustment speed toward equilibrium at 27.5% annually. In the long run, GDP has a significant positive effect, with the signs of GDP² (negative) and GDP³ (positive) confirming an N-shaped EKC. Urbanization and natural resource depletion also significantly worsen environmental degradation. Renewable energy consumption contributes to reducing EF, whereas non-renewable energy consumption slightly increases it. Robustness checks using Augmented Mean Group (AMG) and Common Correlated Effects Mean Group (CCEMG) estimators confirm these findings. The study recommends that policymakers promote renewable energy adoption, implement sustainable urban planning, and enforce stricter environmental regulations to curb ecological degradation in these countries. Lastly, policymakers should recognize the non-linear Environmental Kuznets Curve (EKC) patterns by promoting green growth strategies that decouple economic expansion from environmental degradation.

Keywords: Effect of Environmental, Sustainability Determinants, Ecological Footprint

JEL Classification:

Contribution to/Originality Knowledge:

1.0 Introduction

Over the past few decades, the world has witnessed substantial economic growth, improvements in social welfare, and reductions in energy poverty. However, these achievements have come at a steep environmental cost, particularly due to increased industrialization and unsustainable resource consumption (Hassan et al., 2023). The ecological footprint (EF) a measure that quantifies the environmental demand of human activities has emerged as a critical indicator of environmental sustainability (Yu et al., 2024). Many regions now face ecological deficits, where the EF exceeds local biocapacity, indicating unsustainable environmental practices and resource depletion (Global Footprint Network, 2022).



Sub-Saharan Africa (SSA) presents a paradox. Although the region contributed only 3% of global CO₂ emissions in 2022 and 4% in 2023, it experiences disproportionately severe environmental consequences (Al-Jazeera, 2023). Countries such as Nigeria, Ghana, Kenya, and South Africa exhibit substantial ecological deficits ranging from -77% to -180% as their resource consumption exceeds regenerative capacity (Global Footprint Network, 2023). Moreover, the region's biocapacity has sharply declined from 4.25 global hectares (gha) per person in 1961 to just 0.99 gha per person in 2022, while the ecological footprint has steadily risen to 1.12 gha per person (Shi et al., 2024). This imbalance is driven by urbanization, natural resource depletion, industrial expansion, and increasing reliance on non-renewable energy sources (Akadiri et al., 2022; Ssekibaala & Kasule, 2023).

Despite being endowed with abundant renewable energy potential, SSA continues to rely heavily on fossil fuels, intensifying its ecological stress (Faroukia & Aissaoui, 2024). While several studies have assessed environmental degradation using carbon emissions (Adebayo et al., 2021; Akam et al., 2021), they often overlook the ecological footprint, which provides a more comprehensive view of environmental impact (Joof et al., 2024). Furthermore, the Environmental Kuznets Curve (EKC) hypothesis which posits an inverted-U relationship between economic growth and environmental degradation has been widely tested using CO₂ emissions, but its validity using EF remains underexplored in SSA (Sampene et al., 2022; Sarkodie, 2021; Shen & Yue, 2023). Motivated by the urgent need for sustainable development strategies tailored to SSA's unique ecological challenges, this study aims to evaluate the dynamic effects of environmental sustainability determinants (GDP, urbanization, natural resource depletion, renewable and non-renewable energy consumption) on the ecological footprint in selected SSA countries with high ecological deficits. Additionally, the study investigates whether the EKC hypothesis holds when EF is used as the environmental indicator. The paper is organized as follows: Section 2 reviews the relevant literature. Section 3 presents the theoretical framework and methodology. Section 4 discusses the empirical results and analysis. Section 5 concludes with key policy implications.

2.0 Literature Review

2.1 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 globally. The challenge lies in mitigating this environmental decline without impeding economic progress (Eregba et al., 2023). The Kuznets Curve hypothesis offers a promising theoretical perspective. It suggests that a reduction in environmental pressure can be achieved at a certain level of economic development. The original Kuznets Curve model, proposed by Kuznets (1955), presents an inverted U-shaped relationship between economic income and inequality. In this context, environmental damage is measured through indicators such as ecological footprint. 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. Panel data is frequently employed in such research, and

the typical theoretical representation of the EKC model is often outlined as follows (Grossman & Krueger, 1991; Stern, 2004).

The Environmental Kuznets Curve (EKC) model exhibits different shapes depending on the signs of its various parameters related to income. When all three parameters, β_1 , β_2 , and β_3 , are zero ($\beta_1, \beta_2, \beta_3 = 0$), the relationship between environmental degradation and income is either flat or non-existent. When β_1 is positive and β_2 and β_3 are zero ($\beta_1 > 0, \beta_2 \& \beta_3=0$), the connection is monotonically growing, suggesting that environmental deterioration deteriorates in tandem with economic growth. In contrast, the connection is monotonically lowering if β_1 is negative and β_2 and β_3 are zero ($\beta_1 < 0, \beta_2 \& \beta_3=0$), suggesting that environmental degradation reduces as income increases. The EKC assumes the traditional inverted U-shape when β_1 is positive, β_2 is negative, and β_3 is zero ($\beta_1 > 0, \beta_2 < 0, \beta_3 = 0$). One can detect a U-shaped association ($\beta_1 < 0$ and $\beta_2 > 0$ and $\beta_3 = 0$) where β_1 is negative, β_2 is positive, and β_3 is zero. This study focuses on the EKC's cubic or N-shaped link between income and environmental deterioration when β_1 is positive, β_2 is negative, and β_3 is positive ($\beta_1 > 0$ and $\beta_2 < 0$ and $\beta_3 > 0$). Ultimately, when examining the relationship between economic growth and environmental deterioration, an inverse relationship in the form of a "N" emerges if β_1 is negative, β_2 is positive, and β_3 is negative ($\beta_1 < 0, \beta_2 > 0, \beta_3 < 0$). The EKC model's different forms shed light on the intricate relationship between environmental sustainability and income (Grossman & Krueger, 1991; Stern, 2004).

Building on this foundation, numerous studies have explored the quadratic relationship between pollution and income, taking into account various pollution indicators and environmental degradation measures. The majority of the research on the Environmental Kuznets Curve (EKC) focuses on using GDP or GDP per capita, and their growth rates, to assess the impact of income on indicators like CO₂ emissions and greenhouse gas emissions, primarily related to air pollution. However, these measures often do not include water and soil pollution. Some researchers like Akam et al., (2021); Alqaralleh, (2020); Jian et al., (2022); Sampene et al., (2022); Sarkodie, (2021); Shen and Yue (2023) among others have broadened the horizons by adopting the ecological footprint as a more comprehensive gauge of environmental deterioration. The ecological footprint, initially proposed by Wackernagel and Rees (1996), considers various factors, including carbon footprint, ocean usage, built-up land, grazing land, cropland, and forest land. It quantifies the total natural resources consumed by a population and accounts for the land and water required to sustain human activities and manage waste. This broader approach provides a more encompassing view of the environmental impact of economic development (Lin et al., 2018).

2.2 Empirical Review

Recent studies have extensively examined the relationship between energy consumption, economic growth, and environmental sustainability, employing diverse econometric methodologies across different regions. Adebayo et al. (2022) investigated the effects of renewable and non-renewable energy, economic complexity, and technological innovation on CO₂ emissions, highlighting renewable energy's positive role in environmental quality. Similarly, Adebayo et al. (2021) explored structural change impacts on CO₂ emissions in



Turkey, revealing that while structural change improves ecological quality, fossil fuel reliance remains unsustainable. In Nigeria, Adekunle et al. (2022) found a positive link between economic growth, energy use, and carbon emissions, with unidirectional causality from emissions to growth. Research in Africa and the Middle East further enriches this discourse. Awodumi and Adewuyi (2020) analyzed oil-producing African nations, emphasizing the complex relationship between energy consumption and environmental sustainability. Bargaoui (2021) and Hanif (2018) expanded on these dynamics in the MENA region and Sub-Saharan Africa, respectively, with Hanif confirming the Environmental Kuznets Curve (EKC) and underscoring renewable energy's mitigating effects. Inglesi-Lotz and Dogan (2018) reinforced these findings, showing that non-renewable energy exacerbates pollution, while renewables reduce it in Sub-Saharan Africa's largest electricity producers. Bekele et al. (2024) analyzed 30 Sub-Saharan African countries and found a significant positive long-run relationship between renewable energy consumption and environmental sustainability. Kehu (2023) found that urbanization significantly increases the ecological footprint in Côte d'Ivoire, highlighting the need for green urban development.

Globally, Asıcı and Acar (2016) examined ecological footprint drivers across 116 countries, noting variations based on production and import structures. Pata (2021) focused on BRIC nations, revealing that renewable energy reduces environmental pressure in China and Brazil but not in Russia and India. Saidi and Omri (2020) found nuanced effects of nuclear and renewable energy in OECD countries, while Sowah and Kirikkaleli (2022) highlighted urbanization and trade openness as key factors in environmental sustainability. Uddin et al. (2023) differentiated policy implications for developed and developing nations, stressing financial development and energy consumption's divergent impacts. The EKC hypothesis remains a recurring theme. Sharif et al. (2020) validated it in Turkey, demonstrating that renewable energy reduces ecological footprint, whereas economic growth and non-renewable energy increase it. Nathaniel et al. (2019) found urbanization and growth escalate ecological footprint, while trade degrades environmental quality. Javed et al. (2023) identified green technology innovation and environmental taxes as key reducers of ecological footprint in Italy. Radmehr et al. (2022) reinforced these insights in G7 countries, showing bidirectional links between GDP, renewable energy, and ecological footprint.

Further regional analyses by Sampene et al. (2022) in South Asia confirmed the EKC, with natural resource rents and biocapacity increasing ecological footprint, while renewables mitigated it. Salim et al. (2017) linked urbanization and non-renewable energy to rising emissions in Asia, whereas Ehigiamusoe et al. (2022) identified non-linear financial development and urbanization effects in Africa. Usman et al. (2021) found financial development and renewables reduce ecological footprint in high-emitting nations, contrasting with growth and fossil fuels' adverse effects. Finally, country-specific studies, such as Gupta et al. (2022) in Bangladesh and Samargandi (2021) in Saudi Arabia, highlighted urbanization, energy use, and oil extraction's critical roles in shaping ecological outcomes.

Empirical studies have consistently demonstrated that the relationship between energy consumption, economic growth, and environmental sustainability is complex and context-

specific. Evidence from both global and regional perspectives particularly in Sub-Saharan Africa (SSA), the Middle East, and Asia reveals that non-renewable energy consumption and urbanization tend to exacerbate environmental degradation, while renewable energy and green innovations contribute positively to ecological outcomes. The Environmental Kuznets Curve (EKC) hypothesis is frequently validated, suggesting an inverted U-shaped relationship between economic growth and environmental degradation. Moreover, urbanization, natural resource depletion, and financial development show heterogeneous impacts depending on regional and structural characteristics.

Building on this existing body of literature, this paper contributes to the environmental sustainability discourse by evaluating the dynamic effects of key determinants—GDP, urbanization, natural resource depletion, renewable and non-renewable energy consumption—on the ecological footprint in selected Sub-Saharan African countries with high ecological deficits. Unlike previous studies that often treat SSA as a homogenous group or focus on individual countries, this study targets the most ecologically vulnerable SSA nations, offering a more nuanced understanding of sustainability challenges in the region. By employing dynamic panel techniques, the study captures both short- and long-run effects, providing robust policy-relevant insights into how sustainable development goals can be advanced in high-deficit SSA contexts.

3.0 Methodology

3.1 Model Specification

Based on the literature reviewed following Grossman and Krueger, (1991) and Stern, (2004), the theoretical specification of the EKC model is described as:

$$EI_{it} = \alpha_{it} + \beta_1 Y_{it} + \beta_2 Y_{it}^2 + \beta_3 Y_{it}^3 + \beta_4 Z_{it} + \varepsilon_{it} \quad (1)$$

In the equation 2, 'EI' stands for environmental metrics, ' α_{it} ' represents the constant, ' y_{it} ,' ' y_{it}^2 ,' and ' y_{it}^3 ' symbolize income levels, squared income levels, and cubed income levels, respectively. ' β_1 -k' denotes the estimated coefficients in the regression, 'zit' includes other pertinent indicators for the model, 'i' serves as a spatial identifier (country), 't' represents the temporal marker (year), and ' ε_{it} ' signifies random noise for every country over time.

Following the standard EKC hypothesis, the model specification is:

$$EF_{it} = \alpha_{it} + \beta_1 GDP_{it} + \beta_2 GDP_{it}^2 + \beta_3 GDP_{it}^3 + \beta_4 Z_{it} + \varepsilon_{it} \quad (2)$$

In the equation, ' y_{it} ' represents environmental metrics, ' α_{it} ' symbolizes the constant, ' GDP_{it} ,' ' GDP_{it}^2 ,' and ' GDP_{it}^3 ' stand for gross domestic product, squared of gross domestic product, and cubed of gross domestic product, respectively. ' β_1 -k' signifies the coefficient estimates in the regression, and 'Zit' encompasses other relevant model indicators namely: urbanization, natural resources depletion, renewable and nonrenewable energy consumption. Furthermore, in the extensive body of literature regarding the Environmental Kuznets Curve (EKC), Balaguer and Cantavella (2018) emphasize the ongoing scrutiny and debate surrounding the

accuracy and reliability of income coefficients. Consequently, this study will improve the precision of these estimates by introducing new variables and refining the model specifications. Hence, this study aims to investigate the dynamic impact of urbanization, natural resources depletion, renewable and nonrenewable energy consumption on ecological footprint in selected Sub-Saharan African countries for the period spanning from 1970 to 2023, building upon the work of Adebayo and Rjoub (2021); Adebayo et al., (2022); Danish et al., (2019); Rafique et al., (2021); Sampene et al., (2022), and Shen and Yue (2023) with some modifications. The model functional specification is given below:

$$EF = f(GDP, GDP^2, GDP^3, NR, URB, REC, NREC) \quad (3)$$

The econometric model for functional specification is given as:

$$EF_{it} = \beta_0 + \beta_1 RGDP_{it} + \beta_2 RGDP_{it}^2 + \beta_3 GDP_{it}^3 + \beta_4 URB_{it} + \beta_5 NR_{it} + \beta_6 REC_{it} + \beta_7 NREC_{it} + \varepsilon_{it} \quad (4)$$

Where:

The dependent variable in this study is the Ecological Footprint (EF). while the independent variables include Gross Domestic Product per capita (GDP), the squared (GDP^2), and cubed (GDP^3) terms of GDP per capita, Urbanization (URB), Natural Resource Depletion (NR), Renewable Energy Consumption (REC), and Non-Renewable Energy Consumption (NREC). The error term (ε) represents the stochastic disturbance, i denotes the cross-sectional unit (country), and t indicates the time dimension (year). All variables were transformed into their natural logarithmic forms to achieve linearity and stabilize variance, in line with the approaches adopted by Khan et al. (2020), Ushie and Aderinto (2021), and Shen and Yue (2023). Building on the methodological frameworks of Rafique et al. (2021), Sampene et al. (2022), and Shen and Yue (2023), this study employs the Cross-Sectionally Augmented Autoregressive Distributed Lag (CS-ARDL) model. The model specification for Equation (4) is expressed as follows:

$$\Delta y_{it} = \mu_i + \alpha_i (y_{it-1} - \theta'_i x_{it-1} + \alpha_i^{-1} \eta'_i \bar{y}_t + \dots \alpha_i^{-1} \zeta'_i \bar{x}_t) + \sum_{j=1}^{p-1} \phi_{ij} \Delta y_{it-j} + \sum_{j=0}^{q-1} \delta'_{ij} \Delta x_{it-j} + \sum_{j=0}^{p-1} \nu_{ik} \Delta \bar{y}_{t-j} + \sum_{j=0}^{q-1} \zeta'_{ik} \Delta \bar{x}_{t-j} + \varepsilon_{it} \quad (5)$$

y_{it} is the environmental indicator that is Ecological Footprint (EF). x_{it} is the same 7×1 vector of explanatory variables as described above. (e.g., GDP, GDP square, GDP cube, URB, NR, REC and NREC), all in their natural logarithmic forms. $\bar{y}_t$ and $\bar{x}_t$ are the cross-sectional averages of the explanatory variables and the dependent variable, respectively. θ'_i captures the long-term equilibrium relationship between x_{it} and y_{it} . η'_i and ζ'_i address cross-sectional dependence by incorporating the cross-sectional averages. ϕ_{ij} and δ'_{ij} represent the short-run dynamics and ε_{it} is the error term.

3.2 Method of Data Collection

This study relies on secondary data comprising annual observations from ten Sub-Saharan African countries with the highest ecological deficits, namely: Ethiopia, Burkina Faso, Ghana, Zimbabwe, Nigeria, Benin, Gambia, Kenya, Rwanda and South Africa, each of which exhibits a unique blend of environmental dynamics and socio-economic characteristics. The study will encompass the period from 1970 to 2023.

3.3 Variable Measurement/ Sources

The study employs several key variables to analyze their impact on ecological sustainability. The dependent variable, Ecological Footprint (EF), is measured as ecological footprint per capita in global hectares (gha/person), sourced from the Global Footprint Network (GFN). This variable is widely used in literature, as evidenced by studies such as Shen and Yue (2023) and Sampene et al. (2022). The independent variables include Gross Domestic Product per capita (GDP), measured as real GDP per capita in constant 2015 US\$, obtained from the World Bank. This metric is supported by multiple studies, including Nathaniel (2021) and Ansari et al. (2020). Another independent variable, Urbanization (URB), is measured as the urban population percentage of the total population, also sourced from the World Bank, with references to Nathaniel (2021) and Rafque et al. (2021). Additional independent variables include Natural Resource (NR), measured as natural resource rents (% of GDP) from the World Bank, cited in studies like Sampene et al. (2022) and Ahmad et al. (2022). Renewable Energy Consumption (REC) is measured as the percentage of renewable energy in total energy consumption (in gigajoules per capita), sourced from the International Energy Agency (IEA) and referenced in works such as Adebayo et al. (2022) and Pata et al. (2021). Conversely, Nonrenewable Energy Consumption (NREC) is measured as the percentage of non-renewable energy in total final energy consumption (in gigajoules per capita), also from the IEA, with support from studies like Neagu (2020) and Zafar et al. (2019).

3.4 Techniques of Estimation

The choice of estimation techniques in this study is justified by the presence of cross-sectional dependence and slope heterogeneity, which are common in macro-panel datasets due to globalization, regional spillovers, and economic integration. Ignoring these features can lead to biased and inconsistent estimates. Therefore, before applying any panel econometric models, it is important to conduct diagnostic tests to ensure the validity of underlying assumptions. The study begins with three cross-sectional dependence (CD) tests namely the Breusch-Pagan LM test, Pesaran Scaled LM test, and the Pesaran CD test. These tests help detect the presence of cross-sectional correlations among panel units. In addition, the Pesaran and Yamagata (2008) slope homogeneity test is employed to assess whether the slope coefficients are consistent across cross-sections. These preliminary tests ensure that the panel estimation methods used subsequently are appropriate and robust. Following the confirmation of CD and heterogeneity, the study applies second-generation panel unit root tests to determine the order of integration of the variables. Traditional unit root tests may be invalid under cross-sectional dependence; hence, the study utilizes the Cross-sectional Augmented Dickey–Fuller (CADF) and Cross-sectional Im, Pesaran, and Shin (CIPS) tests. These methods are

specifically designed to account for cross-sectional interdependence and are therefore more reliable for determining stationarity in a panel context. Establishing the stationarity of the variables is crucial for avoiding spurious regression results and for selecting the appropriate model for further analysis.

After confirming the order of integration, the next step involves testing for long-run relationships among the variables. To this end, the study employs the Westerlund (2007) panel cointegration test, which is error correction-based and robust to both cross-sectional dependence and heterogeneity. Unlike first-generation cointegration tests, the Westerlund test does not assume a common autoregressive parameter across the panel and provides both group and panel test statistics. The detection of cointegration validates the existence of a stable long-term relationship among the study variables, despite short-term fluctuations. For the estimation of both short-run and long-run relationships in the presence of CD and heterogeneity, the study adopts the Cross-Sectional Augmented Autoregressive Distributed Lag (CS-ARDL) model. This model is an extension of the conventional ARDL framework, incorporating cross-sectional averages to correct for cross-sectional dependence and to handle endogeneity. The CS-ARDL model is particularly suitable for panels with mixed integration orders ($I(0)$ and $I(1)$) and heterogeneous dynamics, offering efficient and consistent estimates even in complex panel structures.

To reinforce the robustness of the results, the study further applies the Augmented Mean Group (AMG) and Common Correlated Mean Group (CC-MG) estimators. These estimators are designed to accommodate heterogeneity and cross-sectional dependence by allowing for individual-specific long-run relationships and by incorporating common factors. The AMG estimator accounts for unobserved common factors through a dynamic process, while the CC-MG estimator allows for cross-sectional correlation by using cross-sectional averages. Comparing the CS-ARDL results with those from AMG and CC-MG provides a robustness check, ensuring that the estimated long-run relationships are not sensitive to model specification. This multi-model approach increases the reliability and credibility of the empirical findings

3.4.1 Cross-sectional dependency and Slope Homogeneity Test

Before applying panel econometric models, it is crucial to test for cross-sectional dependence (CD) and slope homogeneity to ensure accurate estimations. Due to factors like economic integration, globalization, and spillover effects, panel data often exhibit cross-sectional dependence (Adebayo et al., 2022; Dong et al., 2018). Ignoring CD and slope heterogeneity can lead to biased and inefficient estimates (Talib et al., 2022; Sampene et al., 2022). To address this, the study employs three CD tests: the Breusch-Pagan LM test (Breusch & Pagan, 1980), Pesaran Scaled LM test, and Pesaran CD test (Pesaran, 2004). Additionally, the Pesaran and Yamagata (2008) slope homogeneity test is used to verify whether slope coefficients are consistent across cross-sections. The Breusch-Pagan LM test detects heteroscedasticity and cross-sectional dependence by analyzing residuals from panel regression models. If residuals are correlated across units, CD is present (Breusch & Pagan, 1980). The Pesaran CD test examines contemporaneous correlation among error terms, where the null hypothesis (H_0)

assumes no CD (Pesaran, 2004). The Pesaran Scaled LM test further strengthens CD detection, particularly in larger panels (Pesaran, 2021). For slope homogeneity, the Pesaran and Yamagata (2008) test evaluates whether regression slopes are uniform across groups (H_0 : homogeneity) or vary (H_a : heterogeneity). Failing to account for slope differences can distort model results (Talib et al., 2022). These tests ensure robustness before proceeding with further panel data analysis.

3.4.2 Second Generation Panel Unit root test

Determining the order of integration of each variable is essential for selecting appropriate econometric techniques (Akam et al., 2021). This study employs second-generation panel unit root tests specifically the Cross-sectional Augmented Dickey–Fuller (CADF) and the Cross-sectional Im, Pesaran, and Shin (CIPS) tests to evaluate the stationarity of variables. These tests are well-suited for panel data with cross-sectional dependence, as they account for interdependencies across countries within the same time period and help avoid spurious regression results. By addressing cross-sectional dependence and series heterogeneity, the CADF and CIPS tests enhance the robustness and reliability of the analysis (Sampene et al., 2022; Shen & Yue, 2023). The mathematical formulation of the CADF test is provided in the equation below:

$$\Delta x_{it} = \alpha_{it} + \beta_{it-1} + \beta_{it} + \delta_1 T + \sum_{j=1}^N \gamma_{it} x_{it-j} + \mu_{it} \quad (6)$$

Where x_{it} represents the variables under study, Δ denotes the difference in the variables, and μ_{it} represents the white error term.

The equation for the CIPS test is specified as:

$$\Delta W_{it} = \phi_{it} Z_{i,t-1} + \sum_{i=0}^p \phi_{it} \Delta \bar{W}_{i,t-1} + \sum_{i=0}^p \phi_{it} \Delta W_{i,t-1} + \mu_{it} \quad (7)$$

The mathematical expression for the CIPS test statistics is given by:

$$CIPS = \frac{1}{N} \sum_{i=1}^N \varphi_i(N, T) \quad (8)$$

Null Hypothesis (H_0): All series contain a unit root, i.e., $\alpha_i = 0$ for all i . Alternative Hypothesis (H_1): Some series are stationary, i.e., $\alpha_i < 0$ for $i = 1, 2, \dots, N_1$, and $\alpha_i = 0$ for $i = N_1 + 1, \dots, N$.

3.4.3 Second Generation Panel cointegration test (Westerlund, 2007)

After confirming the stationarity of the variables, the next step in panel data analysis is to assess the existence of a long-run cointegration relationship among the series (Yağlikara, 2022). To address issues of cross-sectional dependence and heterogeneity, this study applied a second-generation panel cointegration test—specifically, the error correction-based

Westerlund (2007) approach. This method is well-suited for handling cross-sectional dependence and provides robust and reliable results regarding long-term equilibrium relationships in panel datasets (Nathaniel et al., 2021; Neagu & Neagu, 2022). The Westerlund test evaluates whether error-correction exists in the panel, with the null hypothesis (H_0) stating that no cointegration is present among the variables. The presence of cointegration suggests that despite short-term fluctuations, the variables share a stable long-run relationship. This approach has been widely employed in recent empirical studies for its reliability in heterogeneous panels (see Adebayo et al., 2022; Akam et al., 2021; Jian et al., 2022; Nathaniel et al., 2021; Sampene et al., 2022; Yağlikara, 2022; Zafar et al., 2019). The mathematical specification of the Westerlund (2007) cointegration model is given as:

$$\Delta Y_{it} = \psi_{it} d_t + \alpha_i (Y_{it-1} - \beta_i X_{it-1}) + \sum_{j=i}^{p_i} \phi \alpha_{ij} \Delta Y_{it-j} + \sum_{j=pi}^{p_i} \phi_{ij} \Delta X_{i,t-j} + \mu_{it} \quad (9)$$

The series trend is represented by $dt = (1, t)$ in this case, and the constant term for all nation series is shown by the elasticity estimates $\psi_i = (\psi_1 \text{ and } \psi_2)$. All cross-sectional dependencies and the study period are denoted by the letters i and t , respectively. The test statistics in the two categories of this approach have the following mathematical expressions:

$$G_t = \frac{1}{N} \sum_{t=1}^N \frac{\eta_i}{S.E(\eta_t)} \quad (10)$$

$$G_a = \frac{1}{N} \sum_{t=1}^N \frac{T\eta_i}{1 - \sum_{j=1}^k \eta_t} \quad (11)$$

The mathematical estimation for the statistics in the panel cointegration approach is expressed as:

$$P_t = \frac{\eta_i}{S.E(\eta_t)} \quad (12)$$

$$P_a = T\eta_i \quad (13)$$

In this case, the abbreviations for the group mean statistics (G_t and G_a) and the panel statistics (P_t and P_a) correspond to their respective sets. The transition adjustment speed from short-term to long-term equilibrium is indicated by the word η_i . It is expected that the corresponding test statistics will be "null," or unrelated to the model variables, and that "there are cointegrating relationships," as the alternative hypothesis.

3.4.4 Cross-sectional Augmented Autoregressive Distributed Lag (CS-ARDL)

The Cross-Sectional Autoregressive Distributed Lag (CS-ARDL) model has gained prominence in empirical research as an effective method for panel data analysis, particularly due to its ability to handle cross-sectional dependence, heterogeneity, and different integration

orders (Adebayo & Rjoub, 2021; Ahmad et al., 2021; Sampene et al., 2022). This model extends the conventional ARDL framework by incorporating the cross-sectional averages of both the dependent and independent variables, thereby mitigating cross-sectional dependence. The CS-ARDL model can be viewed as an ARDL version of the Dynamic Common Correlated Effects (DCCE) estimator, originally developed by Pesaran (2006) and later refined by Chudik and Pesaran (2015). It is especially robust in dealing with endogeneity and cross-sectional correlation, and it allows for the simultaneous estimation of both short-run and long-run dynamics in heterogeneous panels (Chudik et al., 2016). Accordingly, this study adopted the CS-ARDL model, following the formulations proposed by Chudik and Pesaran (2015), and earlier works by Pesaran (2006), Chudik et al. (2013), and Eberhardt and Presbitero (2015). The model was used to explore both the short-term and long-term relationships among the variables, as presented in Equation 5.

3.4.5 Robustness Check using Augmented Mean Group (AMG) and Common Correlated Mean Group (CCMG) Estimator

Using Augmented Mean Group (AMG) and Common Correlated Mean Group (CC-MG) estimators alongside the CS-ARDL model is a recommended approach to enhance the robustness and reliability of panel data analysis, particularly when dealing with heterogeneity and cross-sectional dependence as suggested by Eberhardt and Bond (2009). These estimators provide a solid foundation for estimating long-term relationships and testing for cointegration in panel datasets with multiple entities (Wang & Dong, 2019; Destek & Sarkodie, 2019; Osuntuyi & Lean, 2022). As panel data often exhibit heterogeneity across individual entities. AMG and CC-MG estimators allow for both heterogeneous and homogeneous long-run relationships, thereby capturing the varying dynamics within the panel. (Chudik & Pesaran, 2015). Eberhardt and Bond (2009) emphasize the importance of addressing cross-sectional dependence when dealing with panel data. CC-MG, in particular, takes into account the potential correlation or common factors across entities, which helps mitigate issues related to cross-sectional dependence. Finally, employing both the CS-ARDL model and AMG/CC-MG estimators enables a thorough examination of the data, comparing results from the CS-ARDL model with those from the AMG and CC-MG estimators to evaluate the robustness of the findings. This comparison aids in determining whether the CS-ARDL model appropriately captures long-run relationships in the presence of heterogeneity and cross-sectional dependence (Sampene et al., 2022).

4.0 Results and Discussion

4.1 Cross-sectional Dependency Test Result

In panel data analysis, it is imperative to examine the presence of cross-sectional dependence (CSD), as it captures the extent to which changes in one cross-sectional unit influence others an especially common phenomenon in globally interconnected economic and environmental systems. Neglecting CSD may lead to biased estimations and inefficient model specifications. To investigate CSD in this study, three widely adopted tests were utilized: the Breusch-Pagan LM test, the Pesaran Scaled LM test, and the Pesaran CD test.

Table 1: Cross-sectional Dependency Result

Variables	Breusch-Pagan LM	Pesaran Scaled LM	Pesaran CD
lnEF	770.99***	76.53***	11.26***
lnGDP	850.04***	84.86***	18.79***
lnURB	2248.17***	232.24***	47.37***
lnNR	247.40***	21.33***	9.09***
lnREC	1188.30***	120.51***	28.05***
lnNREC	1059.79***	106.97***	27.06***

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

Source: Authors' Estimation

The results clearly indicate significant cross-sectional dependence across all variables given the significances of all the tests at 1% level, confirming the necessity of utilizing econometric techniques that accommodate cross-sectional dependence.

4.2 Slope Homogeneity Test Result

To evaluate whether the slope coefficients are consistent across cross-sectional units, the Pesaran and Yamagata (2008) slope homogeneity test was employed. This test determines whether the relationships between the variables are homogeneous or heterogeneous across countries.

Table 2: Slope Homogeneity Result

Test Statistic	Value	p-value
Delta	23.93***	0.000
Delta-Adjusted	26.17***	0.000

***, **, and * represent the significance levels at 1%, 5%, and 10%, respectively.
Authors' estimation

Both the Delta and Adjusted Delta statistics are highly significant at the 1% level, rejecting the null hypothesis of slope homogeneity. This confirms that the relationships among the variables vary significantly across countries, reinforcing the need for models that accommodate heterogeneity in the slope coefficients

4.3 Second Generation Panel Unit-root Test Result

Given the confirmed presence of cross-sectional dependence and heterogeneity, first-generation unit root tests would be inappropriate for this analysis. Therefore, the study adopts second-generation panel unit root tests specifically, the Cross-sectional Augmented Dickey-Fuller (CADF) and the Cross-sectional Im-Pesaran-Shin (CIPS) tests to assess the stationarity of the variables.

Table 3: Second Generation Panel Unit-root Test Result

Variables	CADF (Level)	CADF (1st Diff.)	CIPS (Level)	CIPS (1st Diff.)	Order of Integration
lnEF	-1.78	-5.20***	-2.05	-6.09***	I(1)
lnGDP	-1.69	-4.98***	-1.44	-5.73***	I(1)
lnURB	-2.89***	-1.68***	-2.92***	-2.80***	I(0)
lnNR	-1.93	-5.82***	-2.20	-6.19***	I(1)
lnREC	-2.72***	-4.50***	-3.16***	-5.43***	I(0)
lnNREC	-2.33**	-5.06***	-2.66***	-5.30***	I(0)

***, **, and * represent the significance levels at 1%, 5%, and 10%, respectively.

Authors' estimation

The results reveal mixed orders of integration among the variables. Specifically, variables such as lnEF, lnGDP, and lnNR are non-stationary at levels but become stationary after first differencing, indicating integration of order one, I(1). Variables such as lnURB, lnREC, and lnNREC are stationary at level, suggesting integration of order zero, I(0). This combination of I(0) and I(1) variables justifies the adoption of econometric methods such as the CS-ARDL model and the Westerlund (2007) cointegration test, which are robust to mixed integration orders, cross-sectional dependence, and slope heterogeneity.

4.4 Westerlund (2007) Panel Cointegration Test Result

After confirming the presence of stationarity in research variables, the next stage in panel data analysis examines the long-run cointegration of the series under consideration. Given the concerns regarding CSD and heterogeneity, we needed second-generation panel cointegration tests, which offer precise and trustworthy information on the long-run cointegration relationship across variables in various settings. To overcome the earlier issue, the study preferred to apply error correction-based cointegration introduced by Westerlund (2007). The test provides four statistics (Gt, Ga, Pt, and Pa) each offering different insights into the cointegration properties at both the individual and panel levels.

Table 4: Westerlund (2007) Panel Cointegration Result

Statistic	Value	Z value	p value
Gt	-3.186 ***	-1.792	0.007
Ga	-6.953 ***	-3.077	0.000
Pt	9.761***	-2.088	0.001
Pa	8.037 ***	1.244	0.003

***, **, and * represent the significance levels at 1%, 5%, and 10%, respectively.

Authors' estimation

From table 4, the Westerlund (2007) cointegration test was used to examine long-run relationships among the variables. The results provided strong evidence of cointegration at both the individual and panel levels, as all four statistics (Gt, Ga, Pt, and Pa) were significant at the 1% level. This confirms the presence of a long-run equilibrium relationship among the variables, justifying the use of cointegration-based techniques like the CS-ARDL model for

analyzing long-run dynamics. The findings validate the importance of accounting for cross-sectional dependence and heterogeneity in the analysis.

4.5 The CS-ARDL Estimation

After confirming the existence of a cointegration relationship between the heterogeneity and cross sectional dependent variables with mixture of integration among the variables, we can continue to estimate the long run and short-run relationships using the Cross-Sectional Augmented Autoregressive Distributed Lag (CS-ARDL). Table 5 presents the CS-ARDL estimation result.

Table 5: CS-ARDL Estimation Result

Variables	Slope Coefficient	Standard error	Z-Statistics
Long-run			
lnGDP	2.490147***	0.144996	17.17385
lnGDP ²	-0.715597***	0.039938	-17.91786
lnGDP ³	0.054669***	0.002727	20.04451
lnURB	0.127875**	0.053373	2.395887
lnNR	0.121505***	0.027218	4.464197
lnREC	-0.077192***	0.150978	-0.511281
lnNREC	0.004177*	0.066852	0.062484
Short-run			
ΔlnGDP	18.55190***	4.841074	3.832187
ΔlnGDP ²	-2.949378***	0.693453	-4.253178
ΔlnGDP ³	0.157630***	0.032783	4.808325
ΔlnURB	0.989352***	1.667182	0.593428
ΔlnNR	0.002588***	0.015443	0.167610
ΔlnREC	0.007125***	0.320554	0.022229
ΔlnNREC	0.055672***	0.147383	0.377736
ΔECT (-1)	-0.275187***	0.063646	-4.323709

***, **, and * show statistical significance at 1, 5, and 10%, respectively.
Authors' estimation

CS-ARDL estimation results, presented in Table 5. In the long-run coefficients, several variables show statistically significant relationships with EF. GDP has a positive and highly significant effect (2.49, $p < 0.01$), indicating that a 1% increase in GDP leads to a 2.49% increase in EF, strongly confirming that economic growth intensifies environmental pressure in the long term. The GDP² term is negative and significant (-0.72, $p < 0.01$), while GDP³ is positive and significant (0.0547, $p < 0.01$). This non-linear pattern supports the existence of an N-shaped EKC, suggesting that EF initially rises with income growth, then declines, but may rise again at higher income levels. Additionally, natural resource depletion (NR) also has a positive and significant coefficient (0.121505, $p < 0.01$), meaning a 1% increase in NR leads to a 0.122% increase in EF, highlighting the environmental cost of natural resource exploitation. Urbanization (URB) shows a positive and significant coefficient (0.127875, $p < 0.05$), implying that a 1% increase in urbanization leads to a 0.128% increase in EF, indicating

that urban expansion contributes to environmental stress. On the other hand, renewable energy consumption (REC) has a negative and significant coefficient (-0.077192 , $p < 0.01$), suggesting that a 1% increase in REC reduces EF by 0.077%, underscoring the role of renewable energy in mitigating environmental degradation. Lastly, non-renewable energy consumption (NREC) has a positive and marginally significant coefficient (0.004177 , $p < 0.10$), indicating that a 1% increase in NREC leads to a 0.004% increase in EF, showing that reliance on non-renewable energy sources worsens environmental conditions.

In the short-run coefficients, the results reveal stronger immediate impacts of some variables on EF compared to their long-run effects. The immediate impact of GDP is even stronger: a 1% increase in GDP raises EF by 18.55% ($p < 0.01$). This impact is partially moderated by the negative GDP^2 (-2.95) and positive GDP^3 (0.16) terms, which are both significant and indicate a short-run non-linear relationship consistent with the long-run EKC shape. Also, Natural resource utilization (NR) has a positive and significant coefficient (0.002588 , $p < 0.01$), but its impact is smaller in the short run compared to the long run. Urbanization (URB) shows a much stronger immediate impact, with a coefficient of 0.989352 ($p < 0.01$), suggesting that a 1% increase in urbanization leads to a 0.989% increase in EF in the short run. Additionally, Non-renewable energy consumption (NREC) has a positive and significant coefficient (0.055672 , $p < 0.01$), indicating a 1% increase in NREC leads to a 0.056% increase in EF in the short run, which is stronger than its long-run effect. Interestingly, renewable energy consumption (REC) has a small positive and significant coefficient (0.007125 , $p < 0.01$) in the short run, contrasting with its long-run mitigating effect. This could be due to transitional inefficiencies in renewable energy adoption. The error correction term (ECT) has a negative and significant coefficient (-0.275187 , $p < 0.01$), indicating that 27.5% of the disequilibrium in EF is corrected annually, confirming the existence of a long-run equilibrium relationship with a moderate adjustment speed.

The findings confirm an N-shaped Environmental Kuznets Curve (EKC) for ecological footprint in some selected Sub-Saharan African countries aligning with recent empirical studies that challenge the traditional inverted-U hypothesis. The positive GDP, negative GDP^2 , and positive GDP^3 coefficients suggest that while economic growth initially worsens environmental degradation, moderate income levels may temporarily alleviate pressure before higher growth reignites ecological stress. This result is consistent with Fakher et al., (2023), who found an N-shaped EKC for ecological footprints in OPEC countries, emphasizing that non-renewable energy exacerbates environmental damage while renewable energy mitigates it. Similarly, Allard et al., (2018) demonstrated an N-shaped EKC for CO₂ emissions across 74 countries, reinforcing the role of institutional quality and renewable energy in shaping this relationship. The findings also resonate with Wang et al., (2024), who showed that including additional factors like ICT and institutional quality strengthens the N-shaped EKC for carbon emissions globally. However, the results contrast with studies such as Aşıcı and Acar (2018), who found no EKC in 87 countries, and Aydina et al., (2019), who rejected the EKC hypothesis in the EU. These discrepancies highlight the context-dependent nature of the EKC, as noted by Sarkodie (2021). The N-shaped pattern in the study suggests that without proactive policy interventions such as renewable energy adoption and technological innovation economic

growth in Sub-Saharan Africa may lead to recurring environmental degradation, a concern also raised by Muratoğlu et al., (2024) in their sectoral analysis of OECD countries.

Urbanization was also found to increase EF, supporting previous studies by Salim (2017) and Uddin et al. (2017), which identified urbanization as a driver of environmental degradation. The findings align with Kurniawan and Managi (2018) and Gupta et al. (2022), who linked urban expansion to increased resource consumption and pollution. However, Rafque et al. (2021) suggested that investments in human capital and green urban planning could offset some of the negative effects of urbanization on EF. Similarly, Bargaoui (2021) argued that the environmental impact of urbanization depends on factors such as energy efficiency and infrastructure development, suggesting that well-planned urbanization can mitigate environmental stress. Furthermore, while Gupta et al. (2022) focused on urbanization's role in increasing PM_{2.5} pollution, this study specifically examined its impact on EF. Natural resource depletion was another key determinant found to have a strong positive impact on EF, emphasizing the environmental costs of resource exploitation. This result is consistent with findings from Sampene et al. (2022) and Radmehr et al. (2022), who identified resource depletion as a major environmental stressor. Sharif et al. (2020) similarly found that excessive reliance on natural resources significantly affects EF in developing economies. However, studies such as Asıcı and Acar (2016) in more developed regions have shown that improved resource management and technological advancements can decouple resource use from environmental degradation, a trend that is not yet evident in Sub-Saharan Africa. Oghenekaro and Meshack (2021) focused on carbon emissions rather than EF, missing the broader environmental implications of resource depletion.

Energy consumption emerged as a critical factor influencing EF, with renewable energy consumption (REC) reducing EF and non-renewable energy consumption (NREC) exacerbating it. The findings support Saleem et al. (2019), Saidi and Omri (2020), and Usman et al. (2021), who reported that renewable energy plays a crucial role in improving environmental sustainability. Similarly, Sowah and Kirikkaleli (2022) and Adebayo and Rjoub (2021) found that increased adoption of renewable energy reduces environmental degradation, while dependence on fossil fuels worsens it. However, Pata (2021) highlighted the need for country-specific renewable energy policies to ensure their effectiveness. Additionally, studies by Inglesi-Lotz and Dogan (2018) and Javed et al. (2023) provided further evidence that renewable energy reduces CO₂ emissions and EF, particularly in Sub-Saharan Africa and Italy. On the other hand, the significant increase in EF due to non-renewable energy consumption aligns with findings by Awodumi and Adewuyi (2020) and Hanif (2018), who demonstrated that fossil fuel dependence intensifies environmental degradation in African countries.

4.6 Robustness Check using AMG and CCMG

The table 6 presents the results of the Augmented Mean Group (AMG) and Common Correlated Effects Mean Group (CCMG) estimators, which are used to check the robustness of the long-run relationships between the Ecological Footprint and the explanatory variables. Both methods account for cross-sectional dependence and heterogeneity in panel data, ensuring reliable and consistent estimates.

Table 6: AMG and CCEMG Result

Variables	AMG			CCEMG		
	Coefficient	Std. Err.	Z Stat.	Coefficient	Std. Err	Z Stat.
lnGDP	29.4340***	3.5683	8.25	22.3873***	3.6311	6.17
lnGDP ²	-4.5051***	0.5029	-8.96	-3.5020***	0.5118	-6.84
lnGDP ³	0.2306***	0.0234	9.84	0.1836***	0.0238	7.70
lnURB	0.2808988***	0.092391	3.04	1.617271***	0.50614	3.20
lnNR	0.0333776***	0.010431	3.24	0.0275349***	0.006929	3.97
lnREC	-0.1794109**	0.082433	2.17	-0.6227109**	0.275037	-2.26
lnNREC	0.8139752***	0.265474	3.07	2.608174***	1.288798	2.02
Wald chi2(5)	= 39.48***			R-squared (MG) = 0.91		
				F Statistics = 1.68***		
				CD Statistic = -3.61***		

***, **, and * represent the significance levels at 1%, 5%, and 10%, respectively.

Authors' estimation

Robustness checks using the AMG and CCEMG estimators validated the CS-ARDL results. The findings underscore the importance of accounting for cross-sectional dependence and heterogeneity in panel data analysis. From table 6, the AMG results indicate that an increase in GDP substantially increases EF in the long run with coefficient for GDP is 29.4340 ($p < 0.01$). The squared GDP term (GDP²) has a significant negative coefficient of -4.5051 ($p < 0.01$), while the cubed term (GDP³) is significantly positive at 0.2306 ($p < 0.01$). Together, these signs indicate an N-shaped Environmental Kuznets Curve (EKC) at 1% significant level, suggesting that while environmental degradation initially increases with income, it may decline at middle income levels and rise again at higher income levels supporting the findings of de Bruyn et al., (1998). Urbanization also has a significant positive effect, with a coefficient of 0.281 ($p < 0.01$), implying that urban expansion exacerbates environmental stress. Similarly, natural resource utilization is positively associated with EF, as a 1% increase in NR leads to a 0.033% increase in EF ($p < 0.01$), highlighting the environmental costs of resource exploitation. Renewable energy consumption, on the other hand, has a negative and significant impact on EF, with a coefficient of -0.179 ($p < 0.05$), indicating that increased reliance on renewable energy helps mitigate environmental degradation. Non-renewable energy consumption (NREC) has the strongest positive effect on EF, with a coefficient of 0.814 ($p < 0.01$), emphasizing the environmental consequences of fossil fuel dependency. The Wald chi-square statistic ($\chi^2 = 39.48$, $p < 0.01$) indicates that the overall model is statistically significant, confirming that the independent variables collectively explain variations in ecological footprint.

The CCEMG results largely align with those of the AMG model but with some variations in magnitude. The coefficient for GDP remains positive and significant at 22.3873 (Z-statistic: 6.17), while GDP² is negative and significant (-3.5020; Z-statistic: -6.84), and GDP³ remains positive and significant (0.1836; Z-statistic: 7.70). This reaffirms the N-shaped EKC, highlighting the complex relationship between income growth and environmental degradation. Urbanization exerts an even stronger effect on EF in the CCEMG model, with a coefficient of

1.617 ($p < 0.01$), suggesting that urban expansion has a more pronounced environmental impact when accounting for cross-sectional dependence. The effect of NR remains positive and significant (0.028, $p < 0.01$), further emphasizing the environmental costs of resource exploitation. Renewable energy consumption continues to exhibit a negative and significant effect on EF, with a stronger impact (-0.623, $p < 0.05$) compared to the AMG results, underscoring the role of renewable energy in reducing ecological pressure. Also, Non-renewable energy consumption has the strongest positive effect on EF, with a coefficient of (2.608174 $p < 0.05$) showing that reliance on non-renewable energy sources worsens environmental conditions. The R-squared value of 0.91 indicates that the model explains 91% of the variation in EF, demonstrating a strong fit. The F-statistic (1.68, $p = 0.000$) confirms the overall significance of the model, while the significant CD statistic (-3.61, $p = 0.0003$) indicates the presence of cross-sectional dependence, which the CCEMG estimator effectively accounts for.

5.0 Conclusion and policy recommendations

5.1 Conclusion

The paper examined the dynamic effects of economic growth, natural resource depletion, urbanization, and energy consumption on ecological footprint (EF) in 10 Sub-Saharan African countries from 1970 to 2023. The findings reveal that GDP, natural resource depletion, and urbanization significantly increase EF, reinforcing environmental degradation.

The results demonstrate that economic growth exerts a significant and complex non-linear influence on ecological footprint, confirming the existence of an N-shaped Environmental Kuznets Curve (EKC). While renewable energy consumption (REC) helps mitigate EF, its impact remains limited in the short run due to transitional inefficiencies. Non-renewable energy consumption (NREC) further worsens environmental degradation. The error correction term (ECT) indicates a moderate adjustment speed (27.5%) toward long-run equilibrium. Robustness checks with alternative estimators confirm the reliability of these findings. In line with the empirical evidence, the paper concluded by confirming the current growth trajectories, driven by natural resource exploitation, rapid urbanization, and reliance on non-renewable energy, are exacerbating ecological degradation. While renewable energy offers a promising pathway to mitigation, its impact remains constrained by structural and transitional barriers. Lastly the paper support the existence of non-linear pattern of an N-shaped EKC, suggesting that EF initially rises with income growth, then declines, but may rise again at higher income levels

5.2 Recommendation

Policymakers should recognize the non-linear Environmental Kuznets Curve (EKC) patterns by promoting green growth strategies that decouple economic expansion from environmental degradation. This can be achieved by incentivizing businesses to adopt green technologies through tax rebates and subsidies, investing in cleaner industries and sustainable agriculture, and supporting circular economy initiatives such as recycling, reuse, and waste reduction. Also, governments should promote renewable energy adoption by investing in and

incentivizing renewable energy consumption (REC) to reduce reliance on non-renewable energy consumption (NREC) and mitigate environmental degradation. Implementing sustainable urban planning policies, including green infrastructure development, improved waste management, and energy-efficient urbanization, is crucial for minimizing the ecological footprint. Additionally, enforcing strict environmental regulations can help curb excessive natural resource exploitation and reduce industrial pollution. Integrating green economic policies into national development plans will ensure long-term sustainability by balancing economic growth with environmental preservation. Lastly, public awareness campaigns should be conducted to educate citizens and industries on sustainable practices, fostering environmentally friendly behavior and reducing ecological stress.

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