# AN ASSESSMENT OF THE CAUSAL IMPACT OF ENVIRONMENTAL SUSTAINABILITY DETERMINANTS ON THE ECOLOGICAL FOOTPRINT AND BIOCAPACITY IN SELECTED SUB-SAHARAN AFRICAN COUNTRIES

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## ABSTRACT

*This study explores the causal relationships between economic growth, urbanization, resource utilization, energy consumption, and environmental sustainability indicators ecological footprint (EF) and biocapacity (BC) in 10 selected Sub-Saharan African countries with high ecological deficits from 1970 to 2023, using the Dumitrescu and Hurlin (2012) panel causality test. Cross-sectional dependency tests (Breusch-Pagan LM, Pesaran scaled LM, and Pesaran CD) confirm significant interdependence among the variables, while the Pesaran and Yamagata (2008) slope homogeneity test reveals heterogeneous dynamics across countries. Stationarity analysis using second-generation panel unit root tests (CADF and CIPS) shows mixed integration orders. The results reveal both unidirectional and bidirectional causal linkages among EF, BC, and key economic and environmental variables. Specifically, GDP growth and urbanization contribute significantly to environmental degradation, while renewable energy consumption helps mitigate ecological harm. Bidirectional causality between natural resource depletion, EF, and BC further underscores the intricate connection between economic activities and ecological sustainability. These findings support the Environmental Kuznets Curve (EKC) hypothesis. The study recommends increasing renewable energy investment, adopting green urban planning strategies, enforcing strict environmental regulations, and fostering regional collaboration. These interventions are critical for achieving balanced economic development and long-term ecological sustainability in Sub-Saharan Africa.*

**Keywords:** *Ecological Footprint, Biocapacity, Dumitrescu and Hurlin, natural resource*

## 1. Introduction

The relationship between economic growth, energy consumption, urbanization, and environmental sustainability has become a key focus in global sustainability discussions (Hassan et al., 2023). While economic activities drive development, they also contribute to environmental degradation, as seen in the increasing ecological footprint and declining biocapacity worldwide (Global Footprint Network, 2022). Sub-Saharan Africa, despite its relatively low share of global $CO_2$ emissions, faces significant ecological and environmental challenges, with many countries experiencing ecological deficits (Global Footprint Network, 2023; Al-Jazeera, 2023).


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The growing discrepancy between ecological footprint and biocapacity in Sub-Saharan Africa underscores the need to understand the underlying causal relationships between economic growth, resource use, and environmental sustainability (Simionescu & Cifuentes-Faura, 2023). Existing studies have examined the individual impact of factors such as GDP, urbanization, and energy consumption on environmental sustainability (Adebayo et al., 2021; Destek & Sinha, 2020; Talib et al., 2022). However, a comprehensive analysis of the causal interactions among these variables, ecological footprint, and biocapacity remains limited (Ehigiamusoe et al., 2022).

Understanding these causal relationships is crucial for policymakers to develop strategies that promote sustainable economic growth without compromising environmental integrity. This study, therefore, seeks to investigate the causal relationship among environmental sustainability determinants, ecological footprint, and biocapacity in selected Sub-Saharan African countries. By employing advanced econometric techniques, the study aims to provide empirical evidence that can inform policy decisions on sustainable development in the region. The escalating environmental sustainability challenges in Sub-Saharan Africa necessitate a deeper understanding of the interlinkages between key environmental variables, including the ecological footprint, biocapacity, and economic determinants. Environmental sustainability is crucial for long-term economic growth, social well-being, and ecological balance, yet many African countries face significant environmental pressures due to rapid urbanization, industrialization, and resource consumption (Ozkan et al., 2024).

The ecological footprint, which measures the environmental demand imposed by human activities, has consistently exceeded the region's biocapacity, highlighting an unsustainable trajectory (Global Footprint Network, 2023). While biocapacity in Sub-Saharan Africa stood at 4.25 gha per person in 1961, it has since declined to 0.99 gha per person in 2022, while the ecological footprint has risen from 1.48 gha per person to 1.12 gha per person (Shi et al., 2024). This imbalance reflects severe resource depletion, deforestation, biodiversity loss, and increasing carbon emissions. As a result, Sub-Saharan African countries are among the most vulnerable to climate change, facing heightened risks of food insecurity, water shortages, and extreme weather events (IPCC, 2014). A major concern is the impact of economic growth on environmental sustainability. While economic development and industrialization are essential for improving living standards, they often contribute to environmental degradation through increased energy consumption and pollution (Adebayo et al., 2021; Talib et al., 2022). Additionally, the region's high dependence on nonrenewable energy sources, such as fossil fuels, exacerbates environmental challenges, calling for urgent policy interventions to promote renewable energy adoption (African Development Bank, 2022).


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This study seeks to investigate the causal relationships among environmental sustainability determinants, ecological footprint, and biocapacity in selected Sub-Saharan African countries. By analyzing the interconnectedness of these factors, the study aims to provide insights into sustainable development strategies that balance economic growth with environmental conservation. Identifying causality between these variables will help policymakers design effective interventions to mitigate ecological degradation while ensuring long-term environmental sustainability in the region. The relationship between economic growth, energy consumption, urbanization, and environmental sustainability remains a critical yet unresolved issue in Sub-Saharan Africa, particularly in countries facing severe ecological deficits (Ssekibaala & Kasule, 2023). While existing research has examined individual relationships between these factors and environmental degradation (Ameyaw & Yao, 2018; Ardakani & Seyedaliakbar, 2019; Assamoi et al., 2020; Inglesi-Lotz & Dogan, 2018), a comprehensive analysis of their causal interactions remains limited (Marti & Puertas, 2020; Ehigiamusoe et al., 2022; Onifade, 2023). Understanding the causal links between GDP, urbanization, natural resource depletion, renewable and non-renewable energy consumption, ecological footprint, and biocapacity is essential for effective policy formulation (Joof et al., 2024). However, prior studies have largely ignored how these factors influence each other dynamically in the Sub-Saharan African context (Sampene et al., 2022; Williams et al., 2022). Without a clear understanding of these causal relationships, policymakers may struggle to implement strategies that promote both economic growth and ecological balance. This study aims to bridge this gap by exploring the causal relationships among environmental sustainability determinants, ecological footprint, and biocapacity in selected Sub-Saharan African countries with high ecological deficits from 1970 to 2023. The paper is divided into five sections: Introduction, Literature Review, Methodology, Results and Discussions, and Conclusion and Recommendations.

## 2. Literature Review

### 2.1 Theoretical Review

The ImPACT framework (Impact = Population × Affluence × Consumption × Technology) is another extension of the IPAT model. It was developed to address the limitations of IPAT by explicitly incorporating consumption patterns and technological efficiency (Waggoner & Ausubel, 2002). The ImPACT framework extends the IPAT hypothesis by incorporating additional dimensions to better explain environmental impact. One of its key features is the inclusion of Consumption (C), which separates consumption patterns from affluence to more accurately capture the role of consumer behavior in driving environmental degradation. Another important feature is its emphasis on Technology (T), highlighting the role of technological innovation in reducing environmental impact per unit of consumption. Additionally, ImPACT is highly policy-relevant, as it provides a more detailed framework for designing targeted policies that address specific drivers of environmental degradation, such as unsustainable consumption and inefficient technologies (York et al., 2003). These features make ImPACT a valuable tool for understanding and addressing the complex factors influencing environmental sustainability.

The formula is:

$$I = P \times A \times C \times T \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots .1$$

Where: I = Environmental impact, P = Population, A = Affluence, C = Consumption patterns, T = Technological efficiency. ImPACT has been used to analyze the environmental impacts of different consumption patterns, such as dietary choices, transportation, and energy use (Waggoner & Ausubel, 2002). It has also been applied to study the role of technological innovation in decoupling economic growth from environmental degradation (OECD, 2002). ImPACT can help policymakers in Sub-Saharan Africa design strategies to promote sustainable consumption and technological innovation. For example, it can be used to assess the environmental benefits of transitioning to renewable energy and adopting sustainable agricultural practices.

### 2.2 Empirical Review

A broad spectrum of empirical literature has examined the complex relationship between environmental sustainability determinants and ecological footprint across different countries and regions. Nathaniel et al. (2019) found that urbanization and economic growth increase ecological footprint, while trade worsens environmental quality. Sharif et al. (2020), using the QARDL model for Turkey, confirmed the Environmental Kuznets Curve (EKC), showing that renewable energy reduces ecological footprint in the long run, whereas economic growth and non-renewable energy consumption increase it. Javed et al. (2023) reported that green technology innovation, environmental taxes, and renewable energy consumption reduce ecological footprint in Italy, while trade openness and GDP increase it, with all variables Granger-causing EFP. In the G7 countries, Radmehr et al. (2022) observed bidirectional causality between GDP and renewable energy, as well as between ecological footprint and renewable energy. Rafique et al. (2021) found that various socio-economic factors have both positive and negative effects on ecological footprint in the world's top ten economically complex nations. Similarly, Sampene et al. (2022) confirmed the EKC hypothesis in South Asian economies using CS-ARDL and D-H causality tests, showing that natural resource rents and biocapacity increase ecological footprint, while renewable energy reduces it.


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In both developed and developing contexts, energy use and financial development have also shown varied impacts. Uddin et al. (2023) highlighted the differing effects of energy consumption and financial development on ecological footprint across country income groups, emphasizing the need for tailored policy responses. Salim et al. (2017) identified population growth, affluence, and non-renewable energy consumption as key drivers of pollution in Asian developing nations. Focusing on Africa, Ehigiamusoe et al. (2022) revealed non-linear relationships between financial development, urbanization, and environmental degradation, showing both U-shaped and inverted U-shaped effects. Usman et al. (2021) found that financial development, renewable energy, and trade openness help reduce ecological footprint, while economic growth and non-renewable energy use exacerbate it in high-emitting countries. Gupta et al. (2022) demonstrated that urbanization, population density, and energy consumption negatively impact ecological footprint and air quality in Bangladesh, whereas innovation and natural resources mitigate them. In Saudi Arabia, Samargandi (2021) showed that efficient oil extraction can lower ecological footprint and enhance biocapacity, pointing to the significance of sustainable resource management..

## 3. Methodology

## 3. Model Specification

Following the ImPACT framework, this study aims to investigate the causal relationship between environmental sustainability determinants, ecological footprint and biocapacity in selected Sub-Saharan countries for the period of 1970 to 2023, building upon the work of Adebayo et al., (2022) and Sampene et al., (2022) with some modifications. The model functional specification for model one and two are given below:

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

In order estimate the influence of explanatory variables on environmental indicators in the selected Sub Saharan African countries, this study first established an econometric model for functional specifications in equation 2 and 3 as:

$$EF_{it} = \beta_o + \beta_1 GDP_{it} + \beta_2 URB_{it} + \beta_3 NR_{it} + \beta_4 REC_{it} + \beta_5 NREC_{it} + \varepsilon_{it} \quad \ldots 4$$

$$BC_{it} = \beta_o + \beta_1 GDP_{it} + \beta_2 URB_{it} + \beta_3 NR_{it} + \beta_4 REC_{it} + \beta_5 NREC_{it} + \varepsilon_{it} \quad \ldots 5$$

Where:

Ecological Footprint (EF) and Biocapacity (BC) are dependent variables, while independent variables include: Gross Domestic Product per Capita (GDP), Urbanization (URB), Natural Resource Deflation (NR), Renewable Energy Consumption (REC) and Nonrenewable Energy Consumption (NREC). The variables ε represent


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random or stochastic components, while i corresponds to a spatial indicator denoting a specific country, and t signifies the temporal indicator referring to a particular year. All the variables were transformed to their respective natural logarithms following the work of Khan et al., (2020); Ushie and Aderinto (2021). The model specification for Dumitrescu and Hurlin (2012) panel causality test is given as:

$$y_{it} = \sum_{i=1}^{k} \eta_i^{(k)} y_{it-k} + \sum_{i=1}^{k} \lambda_i^{(k)} x_{it-k} + u_{it} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 6$$

As presented in the equation, y and x are considered variables. $y_{it}$ is the dependent variable for country i at time t. Ecological Footprint (EF) or Biocapacity (BC). $x_{it}$ represents the explanatory variables (GDP, URB, NR, REC and NREC), all in their natural logarithmic forms. $\lambda_i^{(k)}$ is the group-specific regression coefficient, $\eta_i^{(k)}$ is the autoregressive coefficient. $y_{it-k}$ is the autoregressive coefficient for the lagged dependent variable. $x_{i,t-k}$ is the group-specific regression coefficient for the lagged explanatory variable. K is the selected lag length. $u_{it}$ is the error term.

**3.2 Method of Data Collection and Sources**

The source of data for this study is secondary in nature covering annual data of ten selected countries in Sub-Saharan Africa with highest ecological deficit namely: Burkina Faso, Zimbabwe, Nigeria, Benin, Ghana, Ethiopia, 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. Furthermore, Data on Ecological Footprint and Biocapacity was obtained from the Global Footprint Network (GFN), while information on Gross Domestic Product per Capita (GDP), Natural Resource Rent, and Urbanization was sourced from the World Bank. In addition, Renewable and Nonrenewable Energy Consumption data was obtained from International Energy Agency (IEA).


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**Table 3.1: Variable definition and Measurement**

| Variable | Measurement | Source | Literature |
|---|---|---|---|
| Ecological Footprint (EF) (DV) | Ecological footprint per capita as global hectares (gha/person). | GFN | Shen and Yue (2023); Sampene et al., (2022). |
| Biocapacity (BC) (DV) | Biocapacity per capita as global hectares (gha/person) | GFN | Shen and Yue (2023); Sampene et al., (2022), Nathaniel (2021). |
| Gross Domestic Product per Capita (GDP) (IV) | Real GDP per capita (constant 2015 US$) | World Bank | Shen and Yue (2023); Sampene et al., (2022), Nathaniel (2021); Ansari et al., (2020). |
| Urbanization (URB) (IV) | Urban population (% of total population). | World Bank | Nathaniel 2021; Rafque et al., (2021); Talib et al., (2022) |
| Natural Resource (NR) (IV) | Natural Resources rents (% of GDP) | World Bank | Sampene et al., (2022); Ahmad et al., (2022); Radmehr et al., (2022) |
| Renewable Energy Consumption (REC) (IV) | Renewable energy is measured by renewable energy as percentage of total energy consumption in in billions of kilowatt-hours per capita. (gigajoule) | IEA | Sampene et al., (2022); Adebayo et al., (2022); Pata et al., (2021) Zafar et al., (2019) |
| Nonrenewable Energy Consumption (NREC) (IV) | Non-Renewable energy is measured by percentage of total final energy consumption in billions of kilowatt-hours per capita (gigajoule) | IEA | Adebayo et al., (2022); Neagu, (2020); Zafar et al., (2019) |

Note that: DV= Dependent variable, IV= Independent variable

### 3.3 Techniques of Estimation

Panel data offers a wealth of insights into dynamic relationships and their impact on various entities over time. To harness the full potential of this data, researchers require a diverse range of advanced statistical techniques. This subsection provides a comprehensive overview of these cutting-edge methodologies. The study employed tests such as the Breusch-Pagan LM, Pesaran LM, and Pesaran CD, as used in Dong et al. (2018), along with the Slope Homogeneity test, following Khan and Bin (2018). These are integral to identifying and addressing issues related to cross-sectional dependency and the homogeneity of slopes across units. Furthermore, second-generation unit root tests including the Cross-sectional Augmented Dickey–Fuller Test (CADF) and the Cross-sectional Im, Pesaran, and Shin Test (CIPS) were explored to assess the stationarity of variables within panel datasets. These techniques are essential for future research endeavors aimed at understanding and analyzing complex panel data, ultimately contributing to more robust and insightful empirical findings. Lastly, the

Dumitrescu and Hurlin causality test provided insights into the direction of causality between variables, a crucial element for effective policy formulation and decision-making.

### 3.3.1 Cross-sectional dependency and Slope Homogeneity Test

Cross-sectional dependence (CD) and slope homogeneity are critical preconditions for selecting appropriate panel econometric models. Cross-sectional dependence arises due to shared characteristics like economic integration, globalization, and spillover effects, which can lead to biased estimates if ignored (Adebayo et al., 2022; Dong et al., 2018). To address this, the study employs three CD tests Breusch-Pagan LM (Breusch & Pagan, 1980), Pesaran Scaled LM, and Pesaran CD (Pesaran, 2004) alongside the Pesaran and Yamagata (2008) slope homogeneity test. Rejection of the null hypotheses for these tests indicates cross-sectional dependence and heterogeneity, necessitating second-generation estimation techniques to ensure reliable results (Talib et al., 2022; Sampene et al., 2022). Given the presence of CD and heterogeneity, the study utilizes second-generation panel unit root tests, including the Cross-sectional Augmented Dickey-Fuller (CADF) and Cross-sectional Im, Pesaran, and Shin (CIPS) tests, to assess stationarity while accounting for cross-sectional dependence (Pesaran, 2007; Chudik & Pesaran, 2015). These tests mitigate spurious regression risks and enhance robustness, ensuring accurate model specification and inference (Akam et al., 2021). By addressing these issues early, the study ensures the validity of subsequent econometric analyses, supporting more reliable policy and empirical conclusions.

### 3.3.2 Second Generation Panel Unit root test

The determination of the integration order of any series is crucial as it guides the application of subsequent analytical techniques (Akam et al., 2021). Two widely used statistical tests for panel data analysis are the Cross-sectional Augmented Dickey–Fuller (CADF) test and the Cross-sectional Im, Pesaran, and Shin (CIPS) test. These tests served to examine specific aspects of the data, focusing on the stationarity of individual units within a panel dataset and addressing cross-sectional dependence by exploring the interrelationships among different cross-sectional units in the same time period. The CADF and CIPS tests play a pivotal role in alleviating concerns related to cross-sectional dependency and preventing spurious results in regression analysis. Additionally, both tests for stationarity assist researchers in assessing the robustness and precision of series heterogeneity. This research utilized second-generation panel root tests, specifically the Cross-sectional Augmented Dickey–Fuller (CADF) and Cross-sectional Im, Pesaran, and Shin (CIPS) tests, to assess the stationarity of the variables. These tests, namely CADF and CIPS, play a crucial role in addressing concerns related to cross-sectional dependency and mitigating spurious results in regression analysis. Additionally, both stationarity tests contribute to the evaluation of the robustness and accuracy of series heterogeneity. The mathematical expression for the CADF test is presented below in Equation 7:

$$\Delta x_{it} = \alpha_{it} + \beta_{it-1} + \delta_1 T + \sum_{j=1}^{N} \gamma_{ij} \Delta x_{it-j} + \mu_{it} \qquad 7$$

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

The equation for the CIPS test is specified as:

$$\Delta W_{i,t} = \emptyset_i + \emptyset_i Z_{i,t-1} + \emptyset_i \overline{Z}_{i,t-1} + \sum_{i=0}^{P} \emptyset_{it} \Delta \overline{W}_{i-1} + \sum_{i=0}^{P} \emptyset_{it} \Delta W_{i,t-1} + \mu_{it} \qquad 8$$

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

$$CIPS = \frac{1}{N} \sum_{i=1}^{N} \varphi_i(N,T) \qquad 9$$

Where the parameter $\varphi_i$ (N, T) represents the CADF regression test statistics. The null and alternative hypotheses for the panel unit root tests are as follows:

Null hypothesis ($H_0$): $\alpha i = 0$ for all $\forall_i$

Alternative hypothesis (H1):

$\alpha i < 0$ for $i = 1, 2, 3, ..., N_1$

$\alpha i = 0$ for $i = N1 + 1, N1 + 2, 3, ..., N$

The application of second-generation panel unit root tests, namely the Cross-sectional Im Pesaran and Shin (CIPS) and Cross-sectional Augmented Dickey-Fuller (CADF) tests is warranted as they address cross-sectional dependence, ensure accurate model specification, enhance model validity and enable robust inference as ignoring cross-sectional dependence can lead to spurious results and inefficient parameter estimates.

### 3.3.3 Dumitrescu and Hurlin Causality Test

The CS-ADRL approach does not allow for the establishment of a causal relationship between series in panel data; it only yields short- and long-term estimates. It is essential to look into the causal relationship in order to advocate integrated and coordinated activities to stakeholders and policy experts. Dumitrescu and Hurlin (2012) causality test was used to examine the causal relationships between the series. In particular, using the methods of (Adebayo et al., 2022; Gyamfi et al., 2021; Jian et al., 2022; Nathaniel et al., 2021; Radmehr et al., 2022; Sampene et al., 2022; Talib et al., 2022). This methodology enabled us to scrutinize the potential presence of common stochastic trends (CSD) and evaluate whether there is inconsistency in the slopes within the research model.

Dumitrescu and Hurlin (2012) introduced this method, and it has gained acceptance and recognition in the econometrics and statistics communities, particularly in cases were traditional tests may fall short. The decision to use the Dumitrescu and Hurlin (D-H) causality test over traditional causality tests can be justified for several reasons: Traditional causality tests, like the Granger causality test, may yield misleading results in the presence of cross sectional dependence (common stochastic trends), leading to spurious causality (Radmehr et al., 2022; Sampene et al., 2022). The D-H causality test is designed to address this issue and provides more reliable results in the presence of cross-sectional dependence. Also, traditional causality tests often assume exogeneity of variables, which may not hold in many real-world scenarios. The D-H test allows for endogeneity, making it more suitable for situations where variables may be interrelated. Moreover, The D-H causality test considers the possibility of changes in the coefficients over time. This is crucial for capturing dynamic relationships between series, which may not be adequately addressed by traditional tests that assume constant coefficients (Nathaniel et al., 2021).

In addition, the D-H causality test is known to provide more accurate inference and is often considered more powerful than traditional tests in detecting causal relationships, especially in panel data settings. More also, The D-H test is specifically designed for panel data analysis, were data points are observed for multiple entities or individuals over time. Traditional tests may not be as well-suited for this type of data. Lastly, D-H test is known for its statistical efficiency, meaning it often requires a smaller sample size to detect causal relationships, which can be advantageous when dealing with limited data (Adebayo et al., 2022; Gyamfi et al., 2021). Therefore, these reasons make D-H causality test more robust and suitable choice for panel data analysis, particularly when accurate inference and statistical efficiency are essential.

Following the work of (Adebayo et al., 2022; Gyamfi et al., 2021; Jian et al., 2022; Nathaniel et al., 2021; Radmehr et al., 2022; Sampene et al., 2022; Talib et al., 2022). The mathematical expression for the generalized form of Dumitrescu and Hurlin can be stated as follows:

$$y_{it} = \sum_{i=1}^{k} \eta_i^{(k)} y_{i,t-k} + \sum_{i=1}^{k} \lambda_i^{(k)} x_{i,t-k} + u_{i,t} \qquad 10$$


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As presented in the equation, y and x are considered variables. K is the lag length, $\lambda_i^{(k)}$ is the group-specific regression coefficient, and $\eta_i^{(k)}$ is the autoregressive coefficient. Wald test statistics can also be used to evaluate the null hypothesis. Z-bar and W-bar statistics are the two statistics that are used in this causation approach. The following are the alternative and null hypotheses under D-H estimation:

$H_0$: $\beta_i = 0$ and $H_1$: $\beta_i \neq 0$.

In the Dumitrescu and Hurlin (D-H) causality test, the null hypothesis states that there is no causal relationship between the variables being examined. On the other hand, the alternative hypothesis contends that the model has a causal relationship.

## 4. Results and Discussion

**Table 1: Cross-sectional Dependency Test Result**

| Variables | Breusch-Pagan LM | Pesaran scaled LM | Pesaran CD |
|---|---|---|---|
| lnBC | 2189.729*** | 226.0743*** | 46.74368*** |
| lnGDP | 850.0437*** | 84.85905*** | 18.79410*** |
| lnURB | 2248.174*** | 232.2350*** | 47.36712*** |
| lnNR | 247.3970*** | 21.33452*** | 9.085401*** |
| lnREC | 1188.300*** | 120.5144*** | 28.05110*** |
| lnNREC | 1059.793*** | 106.9686*** | 27.06191*** |

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

*Authors' estimation (2025)*

In panel data analysis, it is essential to examine whether observations across different cross-sections are interdependent. Cross-sectional dependency (CSD) arises when shocks or changes in one unit influence other units, which is common in globally interconnected economic and environmental systems. Ignoring cross-sectional dependency can lead to biased estimates and inefficiencies in econometric modeling. To assess the presence of CSD in our dataset, we employ three widely used tests: the Breusch-Pagan LM test, the Pesaran scaled LM test, and the Pesaran CD test. The results, presented in Table 1, provide critical insights into the interrelationships among the variables and inform the selection of appropriate econometric techniques.

Table 1 presents the results of cross-sectional dependency (CSD) tests for the variables under study. Cross-sectional dependency examines whether observations in different cross-sections are interdependent. Cross-sectional dependency indicates that the observations across different units (e.g., countries or regions) are not


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independent and may influence one another, which is a critical consideration in panel data analysis. The table includes results from three tests: Breusch-Pagan LM, Pesaran scaled LM, and Pesaran CD. The results show that all variables exhibit significant cross-sectional dependency at the 1% significance level, as evidenced by the high test statistics and their corresponding p-values. For instance, the Breusch-Pagan LM test statistics are exceptionally large for all variables, with BC at 2189.729, and URB at 2248.174, among others. Similarly, the Pesaran scaled LM and Pesaran CD test statistics are also highly significant, further confirming the presence of cross-sectional dependency. Additionally, the Pesaran CD test statistic for BC is 46.74368, for GDP is 18.79410, and for URB is 47.36712, all of which are significant at the 1% level.

The strong evidence of cross-sectional dependency across all variables suggests that the data points are interconnected, likely due to shared global or regional economic, environmental, and social factors. For instance, economic activities (GDP), urbanization, and energy consumption patterns in one country may influence those in neighboring or trading partner countries. Similarly, ecological footprints and biocapacity are often influenced by transboundary environmental impacts, such as climate change or resource depletion, which affect multiple regions simultaneously. Therefore, the findings highlight the importance of accounting for cross-sectional dependency in the analysis to avoid biased or inefficient estimates. Ignoring such dependency could lead to misleading conclusions, as the assumption of independent observations would be violated.

**Table 2: Slope Homogeneity Test Result**

| **Test-Statistics** | **Value** | **p-value** |
|---|---|---|
| **Delta** | 32.324 *** | 0.000 |
| **Delta Adjusted** | 35.345*** | 0.000 |

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

*Authors' estimation (2025)*

In panel data analysis, it is important to determine whether the relationships between the dependent and independent variables are consistent across cross-sectional units. The assumption of slope homogeneity implies that all units share the same underlying economic or environmental dynamics. However, in reality, variations in economic structures, policies, and regional characteristics often lead to heterogeneous relationships. To assess slope homogeneity in our dataset, we employ the Pesaran and Yamagata (2008) test, which evaluates whether the slope coefficients are uniform or vary across cross-sectional units. The results, presented in table 2, provide insights into the appropriateness of using models that account for heterogeneity in the analysis.


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The table 2 presents the results of the Slope Homogeneity Test developed by Pesaran and Yamagata (2008) for the model. This test evaluates whether the slope coefficients across cross-sectional units (e.g., countries or regions) are homogeneous (the same) or heterogeneous (different). Slope homogeneity is an important assumption in panel data analysis, as it determines whether the relationship between the dependent and independent variables is consistent across units or varies significantly. The results show that both Delta and Delta Adjusted statistics are highly significant at the 1% level. The Delta statistic is 32.324 with a p-value of 0.000, and the Delta Adjusted statistic is 35.345 with a p-value of 0.000. These results strongly reject the null hypothesis of slope homogeneity, indicating that the slope coefficients are heterogeneous across the cross-sectional units. The rejection of slope homogeneity implies that the relationship between the dependent variable and the independent variables is not uniform across the units in the dataset. The findings highlight the importance of accounting for heterogeneity in the analysis. Ignoring slope heterogeneity could lead to biased or misleading results, as the assumption of a uniform relationship across units would be invalid.

**Table 3: Second Generation Panel Unit-root Test Result**

| Variables | Level | First Diff. | Order of Integration |
|---|---|---|---|
| **Cross-sectional Augmented Dickey–Fuller Test (CADF)** | | | |
| lnBC | -2.510*** | -5.436*** | I(0) |
| lnGDP | -1.693 | -4.977*** | I(1) |
| lnURB | -2.892*** | -1.679*** | I(0) |
| lnNR | -1.931 | -5.818*** | I(1) |
| lnREC | -2.722*** | -4.503*** | I(0) |
| lnNREC | -2.334** | -5.057*** | I(0) |
| **Cross-sectional I'm Pesaran and Shin Test (CIPS)** | | | |
| lnBC | -3.025*** | -5.886*** | I(0) |
| lnGDP | -1.444 | -5.729*** | I(1) |
| lnURB | -2.919*** | -2.804*** | I(0) |
| lnNR | -2.199 | -6.190*** | I(1) |
| lnREC | -3.160*** | -5.427*** | I(0) |
| lnNREC | -2.657*** | -5.296*** | I(0) |

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

Authors' estimation (2025)

To ensure the reliability of our empirical analysis, it is crucial to examine the stationarity properties of the variables in our panel dataset. Given the presence of cross-sectional dependence and heterogeneity, traditional unit-root tests may not be appropriate. Therefore, we employ second-generation panel unit-root tests, specifically the Cross-sectional Augmented Dickey-Fuller (CADF) and Cross-sectional Im-Pesaran and Shin (CIPS) tests, to determine the order of integration of each variable. Identifying the stationarity properties helps prevent spurious regression results and guides the selection of appropriate econometric techniques. The results of these tests are presented in Table 3.

Table 3 presents the results of second-generation panel unit-root tests, specifically the Cross-sectional Augmented Dickey-Fuller (CADF) test and the Cross-sectional Im-Pesaran and Shin (CIPS) test, to examine the stationarity of the variables. Panel unit-root tests are essential for determining whether the variables are stationary at their levels or require differencing to achieve stationarity. The order of integration indicates the number of differencing operations needed for stationarity. Stationarity ensures that the statistical properties of a variable, such as its mean and variance, remain constant over time, which is critical for obtaining reliable and valid results. The findings indicate that the variables in the dataset exhibit different orders of integration. Variables such as GDP and NR are integrated of order one, I(1), meaning they require first differencing to achieve stationarity. This suggests that these variables have a stochastic trend and may be influenced by long-term economic or environmental processes. On the other hand, variables such as BC, URB, REC, and NREC are integrated of order zero, I(0), meaning they are already stationary and do not require differencing. This implies that these variables are stable over time and may be influenced by short-term or cyclical factors. These findings highlight the importance of employing appropriate econometric techniques to account for mixed integration orders and cross-sectional dependence when analyzing relationships among these variables. Given the mixed order of integration among the variables, we employ the Dumitrescu and Hurlin (2012) panel causality test. This approaches is well-suited for handling panel data with cross-sectional dependence and heterogeneity, ensuring accurate and meaningful estimates.

Table 4 presents the results of the Dumitrescu and Hurlin (2012) panel causality test, which examines the causal relationships between ecological footprint and the explanatory variables (GDP, URB, NR, REC, NREC).

**Table 4 Dumitrescu and Hurlin (2012) Causality Result**

| Direction of Causality | W-Stat. | Z bar-Stat. | Prob. | Remark |
|---|---|---|---|---|
| lnGDP → lnEF | 3.27531*** | 2.82400 | 0.0047 | Unidirectional |
| | 3.24353 | 1.67790 | 0.9034 | |
| lnURB → lnEF | 4.02833*** | 2.81645 | 0.0049 | Unidirectional |
| | 5.39699 | 1.20203 | 0.2606 | |
| lnNR ↔ lnEF | 2.85641*** | 1.11629 | 0.0043 | Bidirectional |
| | 1.78701** | -1.68515 | 0.0315 | |
| lnREC ↔ lnEF | 4.06510 *** | 2.86979 | 0.0041 | Bidirectional |
| | 8.97134*** | 9.98751 | 0.0000 | |
| lnNREC↔ lnEF | 4.33686*** | 3.26404 | 0.0011 | Bidirectional |
| | 4.17005*** | 3.02205 | 0.0025 | |

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

Table 5 presents the results of the Dumitrescu and Hurlin (2012) panel causality test, which examines the causal relationships between Biocapacity and the explanatory variables (GDP, URB, NR, REC, NREC).

**Table 5: Dumitrescu and Hurlin (2012) Causality Result**

| Direction of Causality | W-Stat. | Zbar-Stat. | Prob. | Remark |
|---|---|---|---|---|
| lnGDP ↔ lnBC | 4.14393*** | 2.98415 | 0.0028 | Bidirectional |
| | 4.05150*** | 2.85007 | 0.0031 | |
| lnURB ↔lnBC | 4.95273*** | 4.15751 | 0.0000 | Bidirectional |
| | 9.49549*** | 10.7479 | 0.0000 | |


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| | | | | |
|---|---|---|---|---|
| lnNR → lnBC | 2.49198** | 0.58759 | 0.0168 | Unidirectional |
| | 3.18186 | 1.58844 | 0.2122 | |
| lnREC → lnBC | 4.04660*** | 2.84295 | 0.0005 | Unidirectional |
| | 7.87491 | 8.39687 | 0.1423 | |
| lnNREC↔lnBC | 2.37621*** | 0.41963 | 0.0048 | Bidirectional |
| | 3.22854** | 1.65615 | 0.0177 | |

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

The findings presented in Table 4 reveal strong evidence of unidirectional causality running from GDP to EF at the 1% significance level, as indicated by the W-Statistic (3.27531, $p = 0.0047 < 0.01$). This suggests that economic growth influences EF, but not vice versa, aligning with the Environmental Kuznets Curve (EKC) hypothesis, where economic growth initially leads to environmental degradation. The result is consistent with studies by Usman et al. (2021) and Uddin et al. (2023), which emphasize the negative environmental consequences of economic growth. Similarly, the study finds unidirectional causality from urbanization (URB) to EF at the 1% significance level (W-Statistic = 4.02833, $p = 0.0049 < 0.01$), indicating that urban expansion drives environmental degradation but not the other way around. This finding supports the work of Salim (2017) and Sampene et al. (2022), who highlighted the strain urban expansion places on natural resources.

Additionally, there is evidence of bidirectional causality between natural resource depletion (NR) and EF at the 1% and 5% significance levels, as indicated by the W-Statistic (2.85641, $p = 0.0043 < 0.01$) and Z bar-Statistic (1.78701, $p = 0.0315 < 0.05$). This implies that natural resource exploitation contributes to environmental degradation, while environmental degradation, in turn, affects resource availability and utilization. This bidirectional relationship highlights the interdependence between resource use and environmental sustainability, which is consistent with findings by Radmehr et al. (2022) and Rafque et al. (2021). Moreover, a bidirectional causality is observed between renewable energy consumption (REC) and EF at the 1% significance level (W-Statistic = 4.06510, $p = 0.0041 < 0.01$), suggesting that increased REC reduces EF while environmental degradation drives REC adoption. This feedback loop reflects how environmental concerns incentivize renewable energy adoption, and renewable energy helps mitigate environmental degradation, aligning with Usman et al. (2021). Furthermore, bidirectional causality is evident between non-renewable


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energy consumption (NREC) and EF at the 1% significance level (W-Statistic = 4.33686, $p = 0.0011 < 0.01$), indicating that reliance on non-renewable energy exacerbates environmental degradation, while environmental degradation influences the demand for non-renewable energy. This finding aligns with the results of Adebayo and Rjoub (2021).

Table 5 presents the results of the Dumitrescu and Hurlin (2012) panel causality test for model two, examining the causal relationships between biocapacity (BC) and explanatory variables (GDP, URB, NR, REC, NREC). The results indicate a bidirectional causality between GDP and BC, as evidenced by statistically significant W-statistics (4.14393 and 4.05150) and Z-bar statistics (2.98415 and 2.85007), with probability values of 0.0028 and 0.0031, respectively. This suggests that GDP growth influences BC, while BC also affects GDP, reinforcing the interdependent nature of economic expansion and environmental sustainability. A similarly strong bidirectional relationship is observed between urbanization and BC, with highly significant results (W-statistics of 4.95273 and 9.49549, and Z-bar statistics of 4.15751 and 10.7479, both at a 1% significance level). This implies that urbanization directly impacts BC, and BC, in turn, affects urbanization patterns.

Conversely, unidirectional causality is observed for NR and REC in relation to BC. The results show that NR influences BC (W-statistic = 2.49198, p-value = 0.0168), but the reverse relationship is not significant. This suggests that natural resource depletion has a direct effect on BC, but changes in BC do not significantly impact NR. Similarly, REC has a unidirectional causal effect on BC (W-statistic = 4.04660, p-value = 0.0005), indicating that renewable energy consumption affects BC, but BC does not significantly drive renewable energy consumption. For NREC and BC, the results reveal bidirectional causality, implying that non-renewable energy consumption and BC influence each other. This is reflected in statistically significant W-statistics (2.37621 and 3.22854) and p-values of 0.0048 and 0.0177, respectively. This means that increased dependence on non-renewable energy reduces biocapacity, and changes in BC could also impact non-renewable energy use, possibly through policy responses or resource constraints. The findings highlight bidirectional causality between GDP and BC, reinforcing the interdependence of economic growth and ecosystem regeneration, consistent with Gupta et al. (2022). Similarly, the bidirectional causality between urbanization and BC aligns with Nathaniel (2019), who found that urban expansion affects BC, while BC can influence urbanization patterns. The study also finds unidirectional causality from NR to BC, suggesting that resource depletion negatively affects BC but is not influenced by changes in BC, contradicting Sharif et al. (2020), who found a mutual reinforcement between resource use and environmental degradation. Additionally, the study confirms that while GDP and urbanization are major drivers of EF, renewable energy use mitigates EF and enhances BC.


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These results are consistent with studies by Ehigiamusoe et al. (2022) and Javed et al. (2023), who also found significant causal relationships between economic growth, energy consumption, and environmental outcomes.

**5. Conclusion and Recommendations**

This study examined the causal relationships among economic growth, urbanization, resource utilization, energy consumption, and environmental sustainability indicators in selected Sub-Saharan African countries. The findings highlight the complex interplay between ecological footprint, biocapacity, and key economic factors, revealing that economic growth and urbanization exacerbate environmental degradation, while renewable energy consumption plays a vital role in mitigating it. In light of these insights, there is a need for integrated policy approaches that promote renewable energy investment, reduce dependence on non-renewable sources, and implement eco-friendly urban planning that incorporates green infrastructure. Stricter resource management policies should be enforced to ensure sustainable consumption, while economic growth strategies must be aligned with environmental conservation through tools such as green taxation and carbon pricing. Promoting public awareness about sustainable practices and encouraging behavioral change are also essential. Given the cross-border nature of environmental challenges, enhanced regional cooperation among Sub-Saharan African countries is crucial for the successful implementation of harmonized sustainability policies and effective resource-sharing initiatives. To address these recommendations, a multi-stakeholder approach involving governments, private sector actors, civil society, and regional bodies is essential to design, fund, and implement targeted strategies that foster long-term environmental sustainability across the region.

**References**

Adebayo, T. S., & Rjoub, H. (2021). Assessment of the role of trade and renewable energy consumption on consumption-based carbon emissions: evidence from the MINT economies. *Environmental Science and Pollution Research*, 1-14. https://doi.org/ 10.1007/s11356-021-14754-0

Adebayo, T. S., Altuntaş, M., Goyibnazarov, S., Agyekum, E. B., Zawbaa, H. M., & Kamel, S. (2022). Dynamic effect of disintegrated energy consumption and economic complexity on environmental degradation in top economic complexity economies. *Energy Reports*, 8, 12832–12842. https://doi.org/10.1016/ j.egyr.2022.09.161

African Development Bank. (2022). African Economic Outlook 2022. https://www.afdb.org/en/knowledge/publications/african-economic-outlook

Al-Jazeera (2023). Africa contributes little to global emissions but suffers the most. Available at: https://www.aljazeera.com/news/2023/4/22/africa-contributes-little-to-global-emissions-but-suffers-the-most

Ameyaw, B. & Yao, L. (2018). Analyzing the impact of GDP on CO2 emissions and forecasting Africa's total CO2 emissions with non-assumption driven bidirectional long short-term memory. *Sustainability*, 10, 3110, 1-23. https://doi.org/10.3390/su10093110

Ardakani, M. K., & Seyedaliakbar, S. M. (2019). Impact of energy consumption and economic growth on CO2 emission using multivariate regression. *Energy Strategy Reviews,* 26, 100428, 2-13. https://doi.org/10.1016/j.esr.2019.100428

Assamoi, G. R., Azeez, A. A., Kuepie, M., & Tchegbe, N. R. (2020). Environmental quality, trade openness, and economic growth in Sub-Saharan Africa: A comparative analysis. *Environmental Science and Pollution Research*, 27(15), 17895-17907. https://doi.org/10.1007/s11356-020-08268-7.

Destek, M. A., & Sinha, A. (2020). Renewable, non-renewable energy consumption, economic growth, trade openness and ecological footprint: evidence from organization for economic co-operation and development countries. *Journal of Clean Production,* 242, 118537. https://doi.org/10.1016/j.jclepro.2019.118537

Dogan, E., Ulucak, R., Kocak, E., & Isik, C. (2020). The use of ecological footprint in estimating the Environmental Kuznets Curve hypothesis for BRICST by considering cross-section dependence and heterogeneity. *Science of the Total Environment*, 723, 138063, 1-9. https://doi.org/10.1016/j.scitotenv.2020.138063

Dumitrescu, E. I., & Hurlin, C. (2012). Testing for Granger non-causality in heterogeneous panels. *Economic Modelling,* 29(4), 1450–1460. https://doi.org/10.1016/ j.econmod.2012.02.014

Ehigiamusoe, K. U., Lean, H. H., Babalola, S. J., & Poon, W. C. (2022). The roles of financial development and urbanization in degrading environment in Africa: Unravelling non-linear and moderating impacts. *Energy Reports*, 8, 1665–1677. https://doi.org/10.1016/j.egyr.2021.12.048

Global Footprint Network (2022). Ecological footprint. https://www.footprintnetwork. org/our-work/ecological-footprint/. Accessed 1 June 2024.

Global Footprint Network (2023). World footprint accounts. https://data.footprint network.org/?_ga=2.133565902.1160030786.16113975682001035722.1611397568#/countryTrends?type=BCpc,EFCpc&cn=5001

Gupta, M., Saini, S., & Sahoo, M. (2022). Determinants of ecological footprint and PM2.5: Role of urbanization, natural resources and technological innovation. *Environmental Challenges,* 7, 100467, 1-12. https://doi.org/10.1016 /j.envc.2022.100467

Hassan, S. T., Batool, B., Wang, P., & Zhu, B. & Sadiq, M. (2023). Impact of economic complexity index, globalization, and nuclear energy consumption on ecological footprint: First insights in OECD context. *Energy,* 263, (A), 125628. https://doi.org/10.1016/j.energy.2022.125628.

Inglesi-Lotz, R., & Dogan, E. (2018). The role of renewable versus non-renewable energy to the level of CO2 emissions a panel analysis of sub- Saharan Africa's Big 10 electricity generators. *Renewable Energy*, 123, 36-43. https://doi.org/10.1016/j.renene.2018.02.041

Intergovernmental Panel on Climate Change (2014). IPCC Fifth Assessment Report (AR5). Available at: https://www.ipcc.ch/assessment-report/ar5/

Javed, A., Rapposelli, A., & Khan, F. (2023). The impact of green technology innovation, environmental taxes, and renewable energy consumption on ecological footprint in Italy: Fresh evidence from novel dynamic ARDL simulations. *Technological Forecasting and Social Change*, 191, 122534. https://doi.org/10.1016/j.techfore. 2023.122534

Joof, F., Samour, A., Ali, M., Abdur-Rehman, M., & Tursoy, T. (2024). Economic complexity, renewable energy and ecological footprint: The role of the housing market in the USA. *Energy & Buildings,* 311, 114131, 1-9. https://doi.org/10.1016/j.enbuild.2024.114131

Khan, H., Weili, L., Khan, I., & Oanh, T. K. (2021). Recent advances in energy usage and environmental degradation: Does quality institutions matter? A worldwide evidence. *Energy Reports*, 7, 1091-1103, https://doi.org/10.1016/j.egyr.2021 .01.085

Marti, L., & Puertas, R. (2020). Analysis of the efficiency of African countries through their ecological footprint and biocapacity. *Science and Total Environment,* 722, 137504.

Nathaniel, S., Nwodo, O., Adediran, A., Sharma, G., Shah, M., & Adeleye, N. (2019). Ecological footprint, urbanization, and energy consumption in South Africa: Including the excluded. *Environmental Science and Pollution Research*, 26(26), 27168–27179. https://doi.org/10.1007/s11356-019-05924-2

OECD (2002). *Indicators to measure decoupling of environmental pressure from economic growth*. Organisation for Economic Co-operation and Development.

Onifade, S. T. (2023). Environmental impacts of energy indicators on ecological footprints of oil-exporting African countries: Perspectives on fossil resources abundance amidst sustainable development quests. *Resources Policy*, 82, 103481. https://doi.org/10.1016/j.resourpol.2023.103481

Ozkan, O., Destek, M. A., & Aydin, S. (2024). Evaluating the nexus between energy transition and load capacity factor in Germany: evidence from novel quantilebased approaches. *International Journal of Sustainable Development & World Ecology*, 1-19. https://doi.org/10.1080/13504509.2024.2329224

Radmehr, R., Shayanmehr, S., Ali, E. B., Ofori, E. K., Jasi´nska, E., & Jasi´nski, M. (2022). Exploring the nexus of renewable energy, ecological footprint, and economic growth through globalization and human capital in G7 economics. *Sustainability*, 14, 12227, 1-19. https://doi.org/10.3390/ su141912227

Rafque, M. Z., Nadeem, A. M., Xia, W., Ikram M., Shoaib, H. M., & Shahzad, U. (2021). Does economic complexity matter for environmental sustainability? Using ecological footprint as an indicator. *Environmental Development and Sustainability,* 24, 4623-4640. https://doi.org/10.1007/s10668-021-01625-4

Salim, R. A., Rafiq, S., & Shafiei, S. (2017). Urbanization, energy consumption, and pollutant emission in Asian developing economies: An empirical analysis, ADBI working paper, No. 718, Asian Development Bank Institute (ADBI), Tokyo.

Samargandi, N. (2021). Oil exploration, biocapacity, and ecological footprint in Saudi Arabia. *Environment, Science and Pollution Research,* 28, 54621–54629. https://doi.org/10.1007/s11356-021-14354-y

Sampene, A. K., Li, C., Khan, A., Agyeman, F. O., Brenya, R., & Wiredu, J. (2022). The dynamic nexus between biocapacity, renewable energy, green fnance, and ecological footprint: evidence from South Asian economies. *International Journal of Environmental Science and Technology*, 22, 4471, 1-22. https://doi.org/10.1007/s13762-022-04471-7

Sharif, A., Baris-Tuzemen, O., Uzuner, G., Ozturk, I., & Sinha, A. (2020). Revisiting the role of renewable and non-renewable energy consumption on Turkey's ecological footprint: evidence from quantile ARDL approach. *Sustainable Cities Society*, 57, 102138. https://doi.org/10.1016/j.scs.2020.102138

Shen, Y., & Yue, S. (2023). Does ecological footprint affect biocapacity? Evidence from the experiences of G20 countries. *Natural Resource Modeling*, 12369, 1-18. https://doi.org/10.1111/nrm.12369

Shi, Y., Li, J., Fang, Z., Li, Y., Hu, H., Nie, W., & Meng, F. (2024). Probing the role of natural resources and urbanization towards ecological sustainability in BRICST economies. *Resources Policy*, 91, 104739, 1-8. https://doi.org/10.1016/j.resourpol. 2024.104739

Simionescu, M., & Cifuentes-Faura, J. (2023). Sustainability policies to reduce pollution in energy supply and waste sectors in the V4 countries. *Utilities Policy,* 82, 101551. https://doi.org/10.1016/j.jup.2023.101551

Ssekibaala, S. D., & Kasule, T. A. (2023). Examination of the poverty and environmental degradation nexus in Sub-Saharan Africa. *Regional Sustainability*, 4, 296–308.

Talib, M. N. A., Hashmi S. H., Aamir, M., & Khan, M. A. (2022). Testing non-linear effect of urbanization on environmental degradation: Cross-country evidence. *Frontiers in Environmental Science,* 10, 971394, 1-19. https://10.3389/fenvs.2022.971394

Uddin, I., Ullah, A., Saqib, N., Kousar, R., & Usman, M. (2023). Heterogeneous role of energy utilization, financial development, and economic development in ecological footprint: How far away are developing economies from developed ones? *Environmental Science and Pollution Research,* 30, 58378–58398 https://link.springer.com/article/10.1007/s11356-023-26584-3

Ushie, D. A., & Aderinto, E. R. (2021). Energy consumption, economic development and environmental degradation nexus for Nigeria. *Journal of Life Economics*, 8(4), 463-473. http://doi.org/10.15637/jlecon.8.4.06

Usman, M., Jahanger, A., Makhdum, M. S. A., Balsalobre-Lorente, D., & Bashir, A. (2021). How do financial development, energy consumption, natural resources, and globalization affect Arctic countries economic


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growth and environmental quality? An advanced panel data simulation. *Energy*, 241, 122515. http://doi.org/10.1016/ j.energy.2021.122515

Waggoner, P. E., & Ausubel, J. H. (2002). A framework for sustainability science: A renovated IPAT identity. Proceedings of the National Academy of Sciences, 99(12), 7860-7865. https://doi.org/10.1073/pnas.122235999

Williams, M., Alrub. A. A., & Aga, M. (2022). Ecological footprint, economic uncertainty and foreign direct investment in South Africa: Evidence from asymmetric cointegration and dynamic multipliers in a nonlinear ARDL approach. *Energy & Environment,* 1–15. https://doi.org/10.1177/21582440221094607