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Natural Resource Management and Forest Area Dynamics: A Panel-ARDL Assessment of Environmental Quality in BRICS Nations

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Abstract

This study investigates the impact of natural resource management, forest area, and air & water pollution on carbon dioxide emissions ($LnCO_2$) in BRICS countries (Brazil, Russia, India, China, and South Africa) from 1990 to 2023. It is among the first to comprehensively analyze the interactions between natural resources, forest area, and environmental quality in these nations using advanced panel data techniques. Employing the PMG-ARDL (Pooled Mean Group-Autoregressive Distributed Lag) model, the research examines both short- and long-term dynamics. To address cross-sectional dependence, panel unit root tests (CIPS and CADF) and co-integration techniques (Kao and Johansen) were applied, ensuring robust and reliable findings. Results reveal cross-sectional dependence and mixed stationarity properties among the variables, alongside evidence of a stable, long-term co-integrated relationship. In the long term, natural resource management and forest area significantly affect $LnCO_2$, with decreasing resource rents and shrinking forest areas linked to higher emissions. In contrast, short-term findings show that natural resource management, forest area, and pollution mitigation collectively reduce $LnCO_2$, highlighting their role in promoting sustainability. The findings offer robust policy implications for achieving sustainable development goals (SDGs), particularly those related to climate action and responsible resource consumption, thereby filling a crucial empirical gap in regional and global environmental governance discourse.

Keywords: *Air and Water Pollution; Natural Resource Management; Forest area; $LnCO_2$ Levels; Environmental Sustainability*

Abbreviations

BRICS	Brazil, Russia, India, China, South Afric
CIPS	Cross-section Im-Pesaran
CADF	Cross-section augmented Dickey-Fuller
CO_2	(Carbon di oxide) or Environmental Emissions
FRA;	Forest area
NRM	Natural Resource Management
PAR;	Pollution level of air
PMG-ARDL;	(Pooled Mean Group-Autoregressive Distributed Lag)
PWA;	Pollution level of Water
(VIF);	Variance Inflation Factor

1. INTRODUCTION

Environmental pollution has continued to hinder sustainable development, as it introduces several major environmental issues such as climate change, global warming, deforestation, water scarcity, and various forms of pollution—each of which has posed significant threats since the 1950s. For more than fifty years, nations have been working to address the environmental challenges caused by human activities (Ozcan et al., 2019; Ulucak et al., 2020). In this context, climate change mitigation has become a key priority in many policy agendas. Today, it stands as a global concern, essential for achieving sustainable development, which is seen as a vital pathway for humanity's future (Ulucak et al., 2019; Ulucak et al., 2020). Climate change has emerged as a significant global issue, sparking extensive debate due to its impact on sustainable development Destek snd Sarkodie, (2019). Driven by industrialization and urbanization, the world has seen substantial economic growth in recent decades (Dong et al., 2018), particularly among BRICS nations—Brazil, Russia, India, China, and South Africa. These five emerging national economies are known for their significant influence on regional and global affairs. The term BRIC was first coined by Goldman Sachs economist (Jim O'Neill 2001) who identified these countries as potential drivers of global economic growth. South Africa officially joined the BRIC group in 2010, becoming the fifth member of the grouping, which was then renamed BRICS. Since Goldman Sachs economist (Jim O'Neill 2001), coined the term BRICS has been recognized for its economic growth potential and collective strength, holding 41% of the world's population and 26.7% of the world's land. Together, they account for 23% of global GDP and possess vast natural resources critical for economic and environmental health. These nations, which aim to foster economic cooperation, governance reform, and sustainable development, face complex challenges due to rapid urbanization, industrialization, and resource exploitation, which have led to significant environmental pressures. The recent BRICS Summit (2023) in Johannesburg reaffirmed the group's commitment to sustainable development and climate resilience. BRICS has steadily established itself as a key player in advocating for a multipolar world order based on fairness and international law. As emerging economies, BRICS nations experience both ecological and economic pressures, such as increased carbon emissions, energy consumption, and resource depletion (Kyoto Protocol, 1997). These challenges underscore the need for effective management of natural resources, sustainable forest area measurement, and policies that align economic growth with environmental objectives, as highlighted in Sustainable Development Goal (SDG) 13 on climate action.

BRICS countries face critical environmental challenges driven by high levels of energy consumption, deforestation, and unsustainable natural resource use in sectors like agriculture, mining, and forestry. As these nations transition from ecological surplus to ecological deficit, their impact on global carbon emissions and environmental quality becomes more pronounced. Additionally, the shift to industrialization has increased reliance on fossil fuels, contributing to pollution, forest area loss, and degradation of natural resources. This scenario calls for comprehensive natural resource management and reliable forest area measurement techniques to monitor and mitigate the impacts of deforestation and land degradation. A further complication lies in balancing economic growth with environmental sustainability. In the context of financial development, revenue from natural resources can either enhance or degrade environmental quality, depending on its allocation. The interplay between economic advancement and environmental impact, including greenhouse gas emissions and resource depletion, poses challenges in pursuing sustainable growth without stringent regulations and cleaner production practices.

The study aims to contribute novel insights into the interconnected dynamics of natural resource management, forest area measurement, and environmental quality in BRICS countries. While existing literature has examined the environmental impact of industrialization in emerging economies, gaps remain in understanding the influence of natural resource rents, trade openness, and financial development on environmental outcomes. This research fills these gaps by investigating: how BRICS countries manage their natural resources, this study will assess the implications for environmental quality, providing a foundation for effective policy frameworks, by analysing the effectiveness of current forest area measurement techniques and assess their role in tracking deforestation and land degradation, critical for sustainable land management, by exploring the effectiveness of existing policy frameworks in promoting sustainable practices, identifying opportunities for improvement and alignment with international sustainability goals and by identifying common challenges and areas of mutual benefit, this study highlights avenues for knowledge-sharing and collaboration among BRICS nations, which can enhance environmental resilience.

The study will employ advanced econometric techniques to explore the relationship between economic factors—such as non-renewable energy use, trade openness, and regulatory quality—and environmental outcomes. The findings aim to support evidence-based strategies that bridge the gap between economic development and sustainable resource management, aligning BRICS countries with the goals of international agreements like the Paris Agreement. Through these insights, the research seeks to provide a comprehensive framework for promoting sustainable development in BRICS economies, contributing to global environmental quality and resilience.

This paper focuses on the emerging BRICS economies for several key reasons. Primarily, carbon emissions remain a persistent issue for BRICS governments and environmental advocacy groups (Adedoyin et al., 2020). As Wang and Zhang (2020) note, the last 33 years have seen worsening emissions and environmental degradation in BRICS nations. Research aimed at reducing carbon emissions has produced mixed results, and while numerous policies have been proposed, no consensus has been reached as environmental quality continues to decline. Moreover, there is a notable gap in studies that consider the combined impact of natural resource rents and forest area on carbon emissions in the BRICS context. The interplay of various systems within national economies is an important avenue through which environmental groups can advance sustainable development goals. This study addresses this gap by examining the causal relationships among these variables, including their interactive effects on environmental quality. It extends beyond prior research by modelling the combined impact of natural resource rents and forest area on carbon emissions, alongside other significant factors, such as air and water pollution. Accordingly, this study aims to answer the following research questions: What are the impacts and causal links between natural resource factors and carbon emissions? How do natural resource rents affect environmental quality? What are the interactive effects and causal connections between natural resources, forest area, and environmental degradation?

This paper is structured into five main sections. The first section introduces the topic, setting the foundation for the study. The second section reviews existing literature, offering insights from previous research. The third section details the research methodology, describing the approach and techniques used to conduct the analysis. The fourth section presents the results and discusses their implications in the context of the study's objectives. Finally, the fifth section provides conclusions, summarizing the findings and highlighting their relevance, along with potential areas for further research. This structure facilitates a comprehensive exploration of the research questions.

2. LITERATURE REVIEW:

The literature review examines the management of natural resources and the measurement of forest areas in BRICS countries, emphasizing their impact on environmental quality. It explores how effective resource management and forest conservation can mitigate environmental degradation, highlighting gaps in current research and the need for comprehensive studies in these regions.

2.1 Natural Resource Management and Environmental quality

Natural resource rents, industrial value addition, and total reserves have a significant impact on environmental quality (ENQ), largely due to the adverse effects of resource-intensive industrial activities. This pattern highlights a trend of ongoing environmental degradation linked to industries that rely heavily on natural resources. In contrast, banking development and renewable energy consumption show positive effects on environmental quality, helping to counterbalance these negative influences (Bashir et al., 2024). While fintech and natural resource rents bolster economic recovery, they tend to degrade environmental quality. Renewable energy consumption, however, is associated with both economic growth and environmental improvements, creating a win-win scenario (Zhang et al., 2024). Research focused on BRICS nations shows that urbanization, natural resources, and hydro energy positively influence labor force participation (LF), although economic growth appears to reduce LF (Shi et al., 2024).

Natural resource rents and economic growth in BRICS economies contribute to environmental pollution, as revenues from these resources are often channeled into further economic expansion, leading to higher carbon emissions. On the other hand, green innovation and improvements in energy productivity reduce emissions, promoting better environmental quality Umar and Mirza, (2024). While economic progress and reliance on natural resources are linked to ecological decline, renewable energy use and trade globalization positively impact ecological sustainability, signaling the need for BRICS nations to increase renewable energy use and optimize their natural resource usage (Adebayo et al., 2023).

The connection between natural resource rents, economic growth, and environmental quality is complex, with studies showing bidirectional causality between CO_2 emissions and factors such as the Global Footprint Network (GFN), fintech, and natural resource rents. Additionally, GDP and energy innovation have a one-way causal relationship with CO_2 emissions Udeagha and Ngepah, (2023). For sustainable environmental development, BRICS nations, particularly China, Russia, India, and South Africa, are encouraged to raise the share of renewable energy in their energy mix and support investments in renewable energy infrastructure (Caglar, 2022a).

Research also shows that forest rents, coal rents, and energy efficiency negatively affect sustainable development, while oil rents are a significant contributor to sustainability. Mineral rents, however, have an insignificant impact on development in this context Wang and Razzaq, (2022). Increased trade openness and economic complexity tend to improve environmental quality, whereas economic growth, natural resource exploitation, and public-private partnerships are often associated with environmental degradation (Caglar et al., 2022b).

Education plays a key role in environmental sustainability by promoting clean energy consumption in Brazil, Russia, India, and China over the long term, although this trend has declined in South Africa (Liu, 2022). Long-term data suggests that while economic growth, natural resources, renewable energy, and urbanization have had negative effects on environmental quality in BRICS countries when measured by material footprint, foreign trade and human capital positively contributes to environmental quality Sahoo and Saini, (2021).

2.2 forest area and Environmental quality

GDP growth in BRICS countries has been linked to increased ecological degradation. However, initiatives like Forest Land Conservation Funding (FLCF) and Sustainable Timber Certification (STC) have shown potential to reduce carbon emissions, suggesting that BRICS nations should prioritize forest protection and deforestation prevention. By making structural changes, these countries could better align their economic growth with carbon neutrality goals (Pata, and Isik, 2021; Pata, and Karlilar, 2024).

BRICS countries account for almost one-third of global timber harvesting, with production and export increases, especially from India and China, which have seen a tenfold rise in sawn timber and wood panel exports (Pyzhev, 2023). Due to the geographical remoteness of these nations, improved logistics are essential for facilitating forest product trade, helping them maximize competitive advantages "Research of financial and trade flows of forest industry products taking into account the geographical specificity of countries, (Pyzhev, 2023). This focus on sustainable development within the forest sector aligns with global environmental goals, encouraging cooperation in innovative practices and policies Mochaeva and Chernyakevich, (2022). Despite the promising potential for collaboration, environmental challenges and the need for reindustrialization in processing sectors must be addressed to achieve sustainable growth (Ferreira et al., 2021; Grigorev et al., 2023).

Adopting Sustainable Forest Management (SFM) practices could enhance economic cooperation within BRICS, balancing ecological sustainability with productivity in the forest sector. Integrating SFM strategies would improve resource management, boost forest product trade, and generate jobs, thus fostering economic growth. SFM can mitigate deforestation, promote forest area, and increase forest productivity, enabling economic gains from timber and non-timber products (Numazawa et al., 2020). Given that BRICS countries collectively represent a significant portion of global timber harvesting, there is substantial market potential for sustainable forest products (Pyzhev, 2023). Investments in green technologies and sustainable practices have shown a positive correlation with GDP growth, demonstrating that ecological sustainability can complement economic productivity Li and Tang, (2024). Enhanced logistics and trade agreements could further facilitate the exchange of sustainably sourced forest products, strengthening economic ties (Pyzhev, 2023). Additionally, strategic management of logging residues for bioenergy could create new markets and revenue, integrating economic and environmental objectives (Numazawa et al., 2020).

To promote sustainable practices, coordinated policy efforts across BRICS nations are crucial to achieving maximum economic and environmental benefits (Li et al., 2024). However, the economic effectiveness of SFM varies based on management intensity and forest types, highlighting the need for tailored approaches in each BRICS country (Pulkrab, 2018). While SFM offers significant economic opportunities, challenges like political will, infrastructure investment, and balancing ecological concerns with growth objectives remain critical to successful implementation within the BRICS framework.

Developing forest-economy-driven cooperation among BRICS countries presents both opportunities and challenges. As major timber producers, BRICS nations could boost trade and economic growth through collaboration. However, logistical complexities, diverse regulatory landscapes, and environmental concerns must be managed to unlock this potential. The geographical remoteness of BRICS countries complicates trade logistics, requiring improved transportation networks to ease the flow of forest products (Pyzhev, 2023). Diverse regulatory systems and limited financial commitments also hinder effective cooperation and trade agreements (Rensburg et al., 2015). Sustainable forest resource management is crucial, as overexploitation risks causing ecological harm that could undermine long-term collaboration (Pyzhev, 2023).

Despite these challenges, growing demand for forestry products within BRICS could strengthen economic ties, particularly with countries like China, which heavily depends on imports for its forest product needs (Хуан et al., 2021). Russia's resource abundance complements China's labor-intensive production capacity, fostering a mutually beneficial trade relationship (Хуан et al., 2021). Collaborative research initiatives could further drive innovation in sustainable forestry practices, benefiting all BRICS member nations (Rensburg et al., 2015). The various study, related environmental quality.

The tension between natural resource usage and environmental protection often prompts governments to offer subsidies for fuel consumption, which in turn raises carbon emissions. While natural resource extraction can mitigate environmental harm by fulfilling energy needs and reducing waste discharge into air, water, and soil, understanding the relationship among natural resources, economic development, and CO_2 emissions is essential. This insight is crucial not only for policymakers aiming to curb CO_2 emissions but also for driving growth within the renewable energy sector. Although numerous studies address natural resources' effects on economic growth, few explore their impact on carbon emissions, with available findings often showing mixed outcomes (Balsalobre-Lorente et al., 2018; Hassan et al., 2018). This study addresses this gap by empirically examining the association between natural resources, economic growth, and CO_2 emissions in BRICS countries. Specifically, it introduces natural resources abundance into the analysis, focusing on the interconnection between forest area and CO_2 emissions to address inconsistencies arising from varying levels of economic development. Employing a robust panel estimation technique—the PMG algorithm—and the longest data set available from 1990 to 2023, this study examines each BRICS country separately, yielding results with clear implications for policy.

3. MATERIALS AND METHODS

3.1. Data Description

Building on previous studies (Pata & Isik, 2021; Akadiri et al., 2022; Pata et al., 2023; Chishty, et. al., 2025), this study utilizes $LnCO_2$, an environmental indicator, as the dependent variable. The independent variables include LNRM (natural resource management), LFR (Forest area), LPA (air pollution), and LPW (water pollution), with data obtained from the World Bank database. The analysis centers on Brazil, Russia, India, China, and South Africa (BRICS), using a multivariate annual panel dataset covering the years 1990 to 2023, which aligns with data availability. Table 1 provides detailed variable descriptions, while Figure 1 presents a trend analysis highlighting patterns and variations over time.

Table 1. Descriptive analysis of the variables.

Variable	Signifier	Unit of Measurement	Sources
Environmental Emissions	LCO_2	carbon dioxide damage (% of GNI)	World bank
Natural Resource Management	LNRM	Total natural resources rents (% of GDP)	World bank
Forest area.	LFRA	Forest area (% of land area)	World bank
pollution levels of air	LPAR	air pollution, mean annual exposure (micrograms per cubic meter)	World bank
pollution levels of water	LPWA	Water productivity, total (constant 2015 US$ GDP per cubic meter of total freshwater withdrawal)	World bank

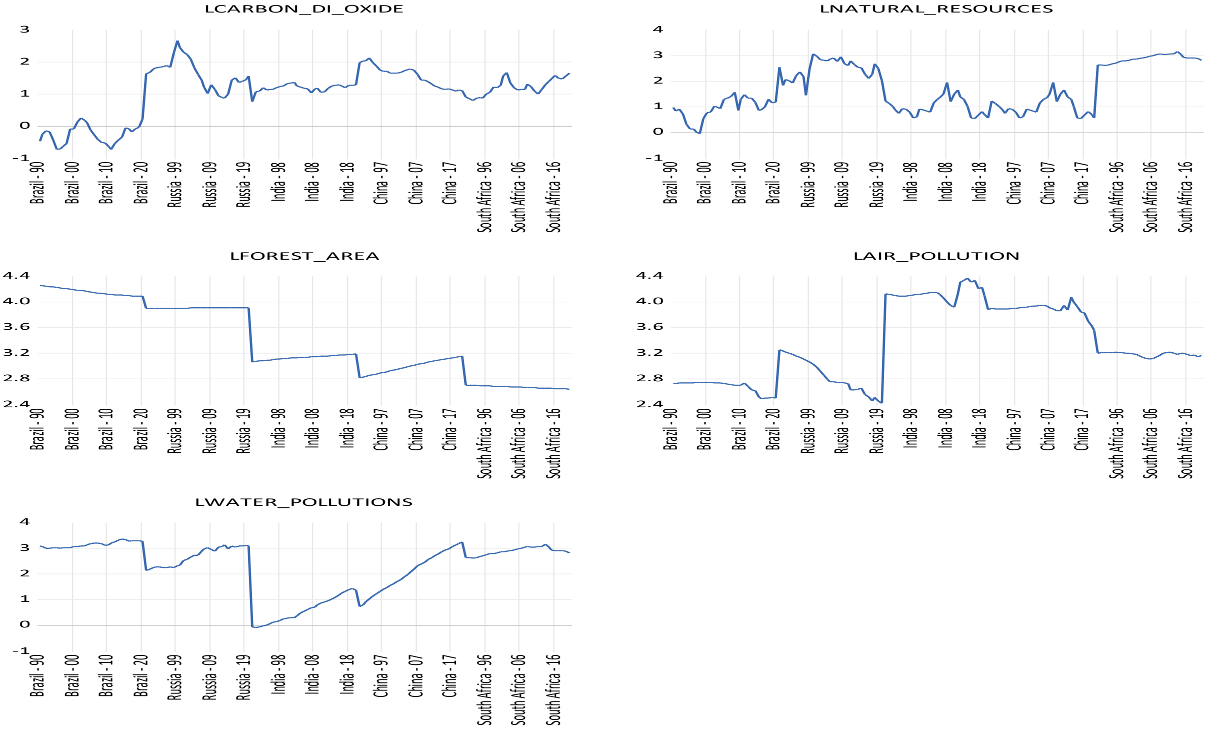


Figure 1: Analysis of trends in patterns and variations.

This table 2 summary provides descriptive statistics for five variables (LCO2, LNRM, LFRA LPAR, LPWA). Each variable's mean, median, maximum, and minimum values give insight into their central tendencies and ranges. Standard deviation shows variability, with LPWA displaying the highest variability (1.018) and LFRA the lowest (0.568). Skewness values indicate asymmetry; LCO2 and LPWA have negative skewness, suggesting a longer left tail, while others are closer to zero. Kurtosis values suggest data shape, with most distributions being platykurtic (kurtosis < 3), except for LCO2. Jarque-Bera and its low probabilities (<0.05) imply non-normality for all variables, which may affect model assumptions.

Table 2. Preliminary statistics of the variables

	LCO_2	LNRM	LFRA	LPAR	LPWA
Mean	1.065	1.663	3.373	3.344	2.274
Median	1.212	1.350	3.143	3.201	2.770
Maximum	2.665	3.162	4.255	4.370	3.358
Minimum	-0.721	-0.038	2.643	2.422	-0.083
Std. Dev.	0.755	0.909	0.568	0.588	1.018
Skewness	-0.850	0.247	0.240	0.143	-0.987
Kurtosis	3.058	1.597	1.450	1.543	2.581
Jarque-Bera	18.670	14.295	17.002	14.237	26.319
Probability	0.000	0.001	0.000	0.001	0.000
Correlation					
LCO2	1.00				
LNRM	0.36	1.00			
LFRA	-0.52	-0.24	1.00		
LPWA	-0.38	0.38	0.37	1.00	
LPAR	0.46	-0.38	-0.64	-0.82	1.00

The table 2, also presents the correlation coefficients between various variables. LCO2 and LNRM have a positive correlation of 0.36, indicating a modest positive relationship. LFRA is negatively correlated with LCO2 (-0.52) and LNRM (-0.24), suggesting that as LFRA values increase, LCO2 and LNRM decrease. LPWA shows positive correlations with LNRM (0.38) and LFRA (0.37), indicating they may move together, though LPWA is negatively correlated with LPAR (-0.82). LPAR has a strong positive relationship with LCO2 (0.46) but is negatively associated with others, implying complex interactions among environmental or economic factors affecting CO_2 and resource management.

3.2. Model Estimation

Building on the empirical framework previously suggested by (Pata and Isik 2021; Jiang et al. 2022; Alhashim et al. 2024), this research develops a log-linear empirical model, as shown in Equation (1), to analyze the effects of relevant factors on environmental emissions.

$$\mathrm{lnCO_2}_{t} = \beta_0 + \beta_1 \mathrm{lnNRM}_t + \beta_2 \mathrm{lnFRA}_t + \beta_3 \mathrm{lnPAR}_t + \beta_4 \mathrm{lnPWA}_t + \mu_t \dots\dots\dots\dots\dots\dots\dots\dots\dots 1$$

Transforming the variables into logarithmic form (denoted by Ln) enabled the determination of elasticity while mitigating issues related to non-normality and heteroscedasticity. In Equation (1), β_0 is the intercept coefficient, β1–β4 are the partial slope coefficients, and μ_t denotes the error term for the period from 1990 to 2023. The coefficient β1 may indicate a positive relationship with LCO2, as reducing the pollution ratio within total energy intensity could enhance environmental quality. The coefficient β2, associated with water pollution, might reflect a negative impact since BRICS countries' heavy reliance on water extraction contributes to both soil and air pollution. For natural resource management, improving the absorptive capacity of crop residue pollutants could bolster environmental quality, suggesting a positive association for the β3 coefficient (Jiang et al., 2022). Furthermore, forest area conservation can elevate property values, health, and welfare, essential factors in which BRICS countries lag compared to developed nations. This paper also investigates the effect of improved environmental quality on economic indicators such as productivity, property values, health, and welfare. Drawing on empirical evidence and case studies, this chapter discusses the economic benefits of investing in environmental protection and sustainability, noting that BRICS nations may experience varying impacts, which will be explored in the findings section. Figure 2 illustrates the hypothesized connections and potential effects of the selected variables on natural resource management and forest area, highlighting their positive or negative impacts on environmental quality (CO2). Additionally, it shows the influence of air and water pollution levels, emphasizing their contributions—both positive and negative—to environmental quality.

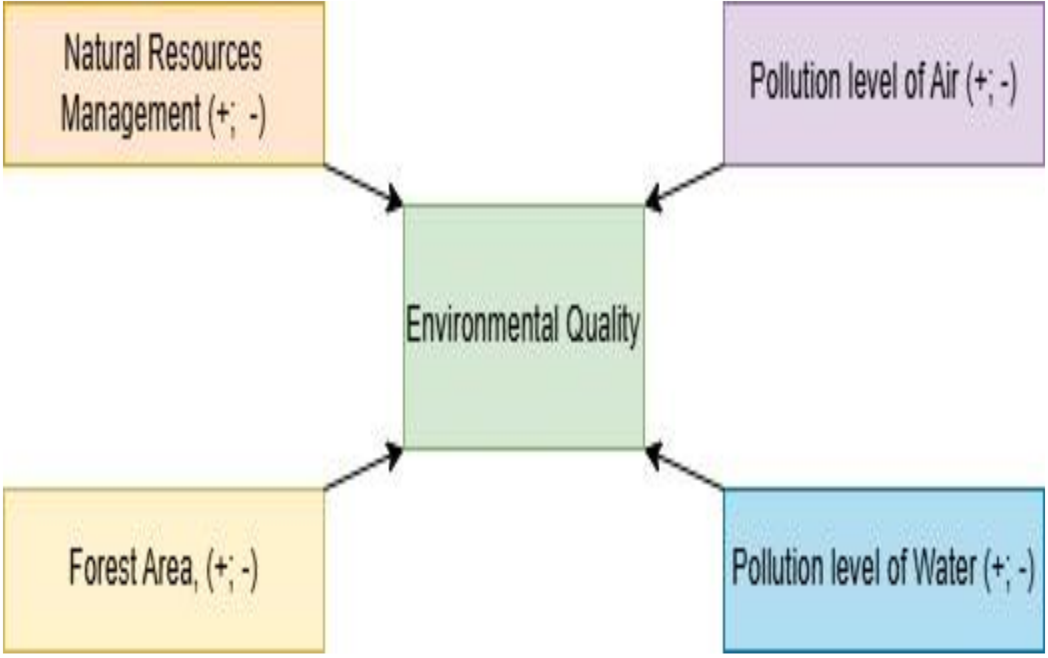


Figure 2 depicts the hypothesized relationships and potential effects of the selected variables on environmental quality. Violet indicates either positive or negative impacts on air pollution (CO2), green represents environmental quality, blue denotes water pollution levels, orange highlights natural resource management, and yellow-orange signifies forest area conservation, showcasing both positive and negative influences on environmental quality.

3.3. ECONOMETRIC METHODOLOGY

The panel dataset in this study, with T > N, facilitates a robust five-stage empirical analysis encompassing: (i) cross-sectional dependence (CSD) tests, (ii) a multicollinearity assessment, (iii) second-generation unit root tests (CIPS and CADF) to evaluate stationarity, (iv) co-integration testing among variables via the Kao test and Johansen Fisher panel co-integration test, and (v) elasticity estimation using the PMG ARDL method. Figure 3 illustrates the methodological flow of this research.

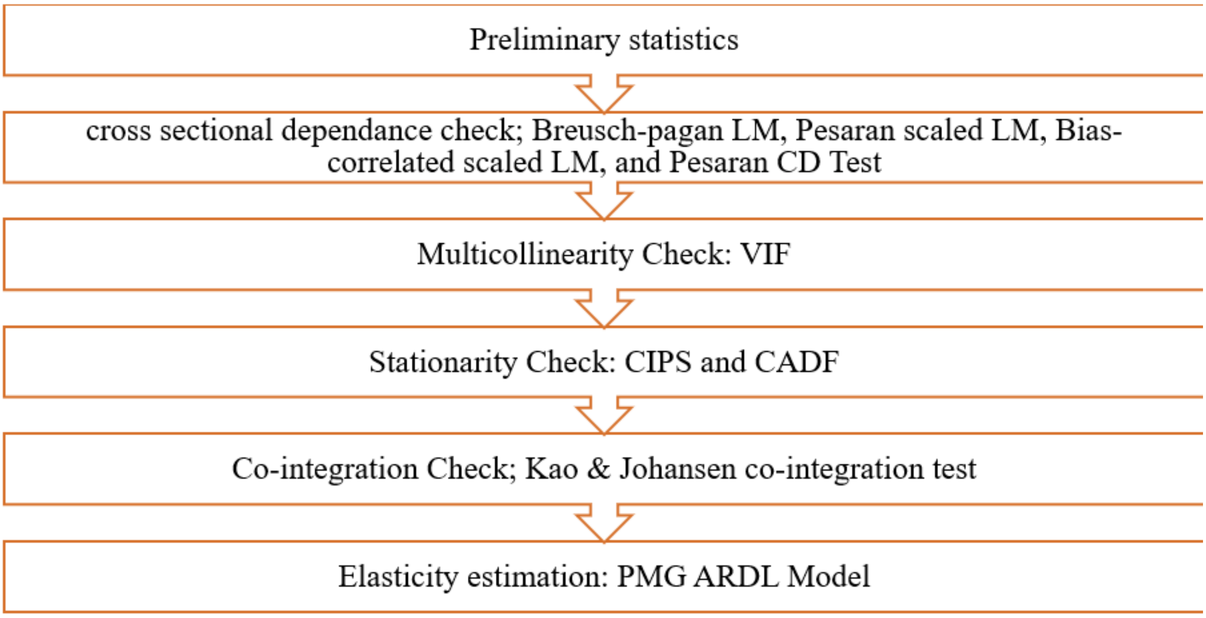


Figure 3. Estimation methodology.

3.3.1. Multicollinearity, CSD, Unit Root, and Cointegration Check

In a regression analysis, multicollinearity—characterized by a high correlation between two or more independent variables—is a common data issue. This can obscure the unique contribution of each variable to the dependent variable, underscoring the need to detect multicollinearity for better statistical clarity. To address this, this study employs Variance Inflation Factors (VIFs). A VIF over four indicates potential multicollinearity, warranting further investigation, although some researchers suggest that a VIF above ten could interfere with reliable coefficient estimation (VIF, 2022).

Since this study uses panel data, it is essential first to assess cross-sectional dependence (CSD). Introduced by (Pesaran 2004), the CSD test examines interdependence among cross-sections, as economic or social factors may drive dependencies across countries in a panel (Chudik & Pesaran, 2013; Andrews, 2005). Ignoring these dependencies and assuming cross-section independence may lead to biased and inconsistent results (Westerlund, 2007). Thus, four different CSD tests are applied here: the (Breusch–Pagan LM 1980), the scaled LM by (Pesaran 2004; Baltagi et al. (2007) bias-adjusted scaled LM, and Pesaran's (2004) CD test. Each test assumes no cross-sectional dependence under the null hypothesis, and examining CSD provides guidance for further tests. For cases where T > N, the Breusch–Pagan LM test is commonly applied as follows:

$$LM = \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} T_{\hat{\rho}} \to X^2 \frac{N(N-1)}{2} \ldots\ldots\ldots 2$$

where the residual covariance matrix's diagonal elements match the degrees of freedom, with T representing the time periods, N denoting the number of cross-sections, and ρˆij = indicating the pairwise correlation between cross-sections. The estimation of cross-sectional dependence (CSD) is then represented as follows:

$$CSD = \sqrt{\frac{2T}{N(N-1)}} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \widehat{\rho ij} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots .3$$

where CSD → N (0, 1) "As (N) approaches infinity and (T) becomes sufficiently large under the null hypothesis of no cross-sectional dependence, the next step in the analysis is to determine the co-integration order of the study variables. In this context, traditional panel unit root tests, known as first-generation tests, may produce unreliable results when cross-sectional dependence is present Dogan and Seker, (2016). To address this issue, (Pesaran 2007) recommended using the cross-sectional augmented IPS (CIPS) and cross-sectional ADF (CADF) tests, which adjust for cross-sectional dependence and yield more accurate results. The CADF and CIPS equations are presented as follows:

$$\Delta y_{it} = \alpha_i + \pi_i y_{i,t-1} + \emptyset_i \bar{y}_{t-1} + \sum_{l=0}^{p} \emptyset_{il} \Delta \bar{y}_{t-1} + \sum_{l=0}^{p} \gamma_{il} \Delta \bar{y}_{t-1} + \varepsilon_{it} \ldots\ldots\ldots\ldots\ldots\ldots 4$$

where y =indicate lagged cross-sectional average; Δy = shows first difference of the lagged cross-section. The CIPS equation is presented in Equation (5):

$$\text{CIPS} = \frac{1}{\text{N}} \sum_{\text{i}=1}^{\text{N}} \text{CADF}_{\text{i}} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots 5$$

"Here, (N) denotes the total number of observations, while CADF represents the cross-sectional augmented Dickey–Fuller value for the i- th individual. After determining the order of integration, it becomes essential to examine potential long-term relationships among the variables (Kao, 1999; Larsson et al., 2004). This study applies both the Kao and Johansen Fisher panel co-integration tests to evaluate the stability of long-term associations within the data series. Kao's residual-based test specifies individual cross-sectional intercepts and assumes homogeneous weights for the initial regressors (Kao, 1999). Additionally, the study employs the Johansen-type test proposed by Maddala and Wu (1999), which aggregates test statistics across cross-sections to produce a unified panel test statistic. This test involves two metrics: the Fisher statistic from the trace test and the Fisher statistic from the maximum eigenvalue test, with three lag orders considered for this analysis.

3.3.2. Pooled Mean Group–Autoregressive Distributed Lag (PMG-ARDL) Model

This study estimates both short-run and long-run effects. In panel data models, standard ARDL methods are prone to bias due to the correlation between mean-differenced independent variables and the white noise error term (Bekun et al., 2019). To address this, the ARDL approach is combined with the Pool Mean Group (PMG) estimator introduced by (Pesaran et al.1999), which offers greater resilience to lag order selection and outliers, making it a robust estimation method overall (Pesaran et al., 1999). The PMG estimator is effective when the dataset contains variables of mixed integration orders, I(0) and I(1), but not I(2). This approach yields heterogeneous short-run effects and homogeneous long-run effects. Using the PMG-ARDL model, Equation (1) was analyzed in the following error correction model (ECM) form:

$$\Delta \text{lnCO}_{2\,\text{i,t}} = \emptyset_{\text{i}} \text{ECT}_{\text{i,t}} + \sum_{\text{j}=0}^{\text{q}-1} \overline{y\,*}_{\text{i,j}}\, \Delta \text{LnX}_{\text{i,t}-\text{j}} + \sum_{\text{j}=0}^{\text{q}-1} \overline{\delta\,*}_{\text{i,j}}\, \Delta \text{LnCO}_{2\text{i,t}-\text{j}} + \mu_{\text{i,t}} \dots\dots\dots\dots\dots .6$$

Were

$$\text{ECT}_{\text{i,t}} = \text{lnCO}_{2\text{i,t}-\text{j}} - \emptyset_{\text{i,}} \text{X}_{\text{i.t}} \dots\dots\dots\dots\dots\dots\dots\dots\dots .7$$

$$\emptyset_{\text{i}} = -(1 - \sum_{\text{j}=1}^{\text{p}} \delta_{\text{i,j}})$$

$$\theta_{\text{i}} = -\frac{\sum_{\text{j}=0}^{\text{q}} \delta_{\text{i,j}}}{\emptyset_{\text{i}}}$$

$$\overline{y\,*}_{\text{i,j}} = -\sum_{\text{d}=\text{j}+1}^{\text{p}} \delta_{\text{i,d}}$$

$$\overline{\delta\,*}_{\text{i,j}} = -\sum_{\text{d}=\text{j}+1}^{\text{q}} \gamma_{\text{i,d}}$$

In this model, Δ denotes the difference operator, with LnCO_2 representing the dependent variable, which is the load capacity factor. For each cross-sectional unit i in t, a set of independent variables (NR, TI, RE, EA) is represented by X with a uniform lag length q. The parameters φ and θ are represent the adjustment and long-run coefficients, respectively. Upon achieving convergence, these coefficients produce $\gamma *$ and $\delta *$; while the error term is denoted by μ

4. EMPIRICAL FINDINGS AND DISCUSSION

This section presents the empirical results from various econometric tests. First, the study examines multicollinearity among the variables using VIF, with results displayed in Table 3. As all VIF values are below four, and the mean VIF is well below this threshold, it suggests that multicollinearity is either minimal or likely absent in this analysis.

Table 3. VIF test.

Variables	VIF
LNRM	2.2
LFRA	3.59
LPAR	7.59
LPWA	3.49
Mean VIF	4.21

In the subsequent stage of this empirical analysis, the results of the cross-sectional dependence (CSD) tests are presented in Table 4. The purpose of conducting CSD tests is to determine whether a disruption within any of the entities represented (such as a country) could create a ripple effect across other entities due to their interdependence, subsequently impacting their economic conditions. This concept of mutual reliance is particularly relevant in studies focused on topics like carbon emissions, as many countries depend on each other for access to newly developed technological tools and support. Addressing CSD is essential in panel data analysis to ensure valid results (Agubata et al., 2022). To account for this interdependence, this study uses four distinct tests to assess the presence of CSD: the Breusch–Pagan LM test (1980), the (Pesaran 2004) scaled LM test, the (Baltagi et al. 2007) bias-corrected scaled LM test, and the (Pesaran 2004) CSD test. As shown in Table 4, the results from all four tests indicate significant CSD within the dataset, confirming acceptance of the alternative hypothesis of cross-sectional dependence among the study variables.

Table 4. Cross-sectional dependence tests.

	Variables				
Test	LnCO2	LnNRM	LnFRA	LnPAR	LnPWA
Breusch-Pagan LM	74.94*** (0.00)	122.17*** (0.00)	297.43*** (0.00)	50.84*** (0.00)	229.23*** (0.00)
Pesaran scaled LM	14.52*** (0.00)	25.082*** (0.00)	64.27*** (0.00)	9.13*** (0.00)	49.02*** (0.00)
Bias-corrected scaled LM	14.43*** (0.00)	24.99*** (0.00)	64.18*** (0.00)	9.05*** (0.00)	48.94*** (0.00)
Pesaran CD	3.30*** (0.00)	10.78*** (0.00)	-3.55*** (0.00)	4.13*** (0.00)	15.00*** (0.00)

Note: Null hypothesis (H0) of no cross-sectional dependency is rejected for all variables at a 1% significance level (corresponding p value).***p<0.01.

This study's empirical analysis also requires evaluating the stochastic properties of each variable, using stationarity tests to verify them. Given the presence of cross-sectional dependence (CSD) across the data sections, using first-generation unit root tests is discouraged, as they may produce unreliable outcomes. Instead, the second-generation unit root tests—CIPS and CADF—are applied in this phase. The PMG-ARDL model, which is employed here, necessitates that the study variables have integration orders at level [I(0)] or at first difference [I(1)], rather than at second difference [I(2)]. The unit root test results, summarized in Table 5, confirm this requirement, with all variables meeting the expected stationarity levels in both CIPS and CADF tests. Notably, all variables are stationary at their respective levels except for natural resource rent, which attains stationarity at the first difference. Thus, both unit root tests suggest a mixed integration order across the data series.

Table 5. Stationarity check.

Variable	CIPS		CADF	
	Level	First	Level	First
LnCO2	-0.53	-4.7***	9.98	41.22***
LnNRM	-0.59	-6.58***	10.2	59.47***
LnFRA	-245.24***	-248.04***	23.50***	22.51***
LnPAR	1.66	-2.75***	8.2	25.01***
LnPWA	0.12	-3.36***	7.86	29.37***

Note: Level and reported stationarity at the level and at first difference, respectively. ***p<0.01.

This study investigates the long-term equilibrium relationship to determine if the variables under examination demonstrate convergence. To achieve this, the Kao residual co-integration test was used, with results presented in Table 6. The test findings indicate a time-stable equilibrium relationship among LCF, natural resource rent, renewable energy consumption, technological innovation, and employment in agriculture, supporting the alternative hypothesis of long-term co-integration at a 1% significance level. Additionally, the Johansen–Fisher test was applied to further explore this long-term relationship. As shown in Table 7, the Johansen–Fisher test results align with those of the Kao test, affirming a long-term co-integration relationship between LCF and the selected independent variables for the period 1992–2020 across BRICS nations.

Table 6. Kao residual co-integration test.

	t-Statistic	Prob.
ADF	-2.32151	0.0101
Residual variance	0.017405	
HAC variance	0.025386	

Notes: ***p<0.01.

Table 7. Johansen–Fisher panel co-integration test results.

Hypothesized No. of CE(s)	**Fisher Stat.* (from trace test)**	**Prob.**	**Fisher Stat.* (from max-eigen test)**	**Prob.**
None	60.74***	0.00	39.55***	0.00
At most 1	27.92***	0.0005	17.08***	0.0293
At most 2	16***	0.0424	12.96	0.1131
At most 3	10.4	0.2381	6.445	0.5976
At most 4	15.56***	0.0491	15.56***	0.0491

Notes: ***p<0.01.

After confirming the prerequisite of long-term co-integration among the variables, the analysis advanced to assess the degree of these co-integrations by estimating the coefficients. Consequently, the short-term and long-term impacts of the predictor variables on LCF were examined using the PMG-ARDL model, as shown in Table 8. The results, with a convergence rate of 27%, indicate robust and reliable forecasting. This convergence rate reflects the impact of the explanatory variables on their respective equilibria. The statistically significant error correction term (ECT) further validates a balanced relationship among the parameters, with approximately 27% of deviations from equilibrium being corrected annually.

Table 8. PMG-ARDL results.

Long run estimation				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
LnNRM	0.094***	0.036	2.594	0.010
LnFRA	-0.011**	0.014	-0.762	0.047
LnPAR	-0.060***	0.021	-2.818	0.006
LnPWA	-0.249***	0.031	-7.936	0.000
Shot run estimation				
LnNRM	0.62***	0.07	9.30	0.00
LnFRA	-4.17***	1.22	-3.43	0.00
LnPAR	1.03***	0.19	5.40	0.00
LnPWA	-0.06*	0.07	-0.86	0.09
ECT(-1)	-0.27**	0.14	-2.00	0.05

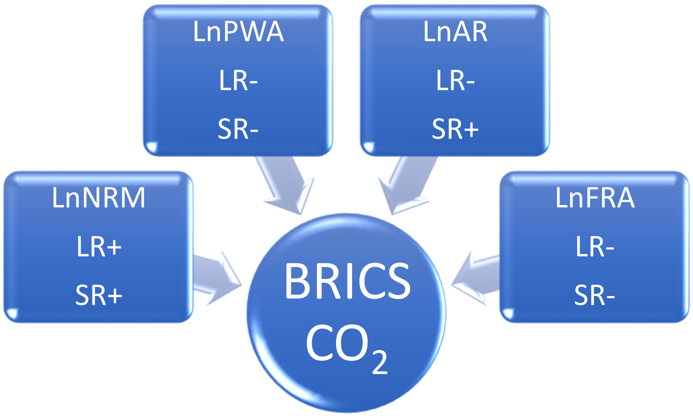
Notes: ***p<0.01, **p<0.05.

The PMG-ARDL estimation reveals that, in the long term, all parameters have an significant effect on LCO_2, while in the short term, all factors also show a statistically significant influence on LCO_2. environmental impact of natural resource management, there is no significant short-run effect on LCO_2

across the sampled countries. However, in the long term, natural resource use significantly worsens environmental conditions in BRICS countries, with each 1% increase in natural resource use leading to a 0.09% increase in environmental degradation. This finding aligns with previous research by (Pata & Isik 2021; Ni et al. 2022; Wang & Razzaq, 2022), suggesting that revenue generated from resource extraction and processing substantially contributes to the environmental degradation BRICS countries face, as these funds are reinvested in industrial expansion. Rapid economic growth has driven industrialization and a heightened demand for raw materials, intensifying air pollution and deforestation. The heavy reliance of BRICS nations on industrial output has led to extensive natural resource extraction and fossil fuel use, with countries like Russia, China, and Brazil, among the world's largest producers and consumers of natural resources, seeing significant environmental pollution due to their dependence on oil, natural gas, and coal-based power. However, BRICS nations show a significant negative effect of forest area on $LnCO_2$, with a long-term $LnCO_2$ decrease of 0.01%. However, forest area also short-term significance, likely due to its complex, time-intensive nature. Despite the PMG-ARDL findings indicating that forest area may not support long-term sustainability, increased resource use may elevate emissions, indicating limited conservation efforts in BRICS nations. Forest area initiatives tend to prioritize conservation, sometimes at environmental quality's expense, contributing to atmospheric pollution. Transitioning to eco-friendly technologies also demands considerable time. These findings align with (Adebayo et al. 2022), while Awosusi et al. (2023) found forest area positively impact $LnCO_2$, boosting environmental sustainability. Results indicate a negative, statistically significant long-term relationship between water pollution and $LnCO_2$, whereas in the short term, this relationship is significant but positive, implying that air pollution immediately impacts BRICS' natural environment. Specifically, a 1% increase in air pollution improves long-term $LnCO_2$ by 0.06%, while in the short term, a 1% increase in air pollution reduces it by 1.03%, likely due to the growing environmental awareness among BRICS nations. This shift, linked to increased eco-friendly practices, has contributed to a slowdown in environmental degradation in BRICS countries (Farhani & Shahbaz, 2014; Çıtak et al., 2021). Furthermore, air pollution offers reliability and sustainability, promoting environmental benefits by reducing CO_2 and other GHG emissions, thus sustaining progress without significant delays. However, certain member countries, such as China and South Africa, continue to face challenges in reaching substantial eco-friendly milestones.

Regarding the Table 8 reveals that water pollution coefficients are statistically significant, showing negative effects in both the short and long term. Specifically, for each unit reduction in water pollution, BRICS nations increase their $LnCO_2$ by 0.24% in the short run and 0.06% in the long run. Environmental quality is greatly impacted by water pollution, particularly in industrial areas, which are primary pollution sources. Additionally, reduced water pollution contributes to lower atmospheric CO_2, as carbon is sequestered in soil, and crop plants help reduce dust levels. Farmland hedgerows and riparian zones, like riverbanks, contribute to forest area due to heightened agricultural activity. Therefore, water pollution control enhances the environment's resilience and absorption capacity. Conversely, (Jiang et al. 2022) argue that water pollution harms environmental quality, leading to deforestation and waste production, causing soil and water contamination.

Figure 4 summarizes the PMG-ARDL model outcomes.



Figure, 4 Summary of the PMG-ARDL estimations. Note: S R refers to short run; LR is long run; LCF represents the load capacity factor; '/'indicates the effect is null;'+'and' 'indicate positive effect and negative effect.

5. CONCLUSIONS AND POLICY INSIGHTS

5.1 Concluding remarks

This study seeks to deepen the understanding of how air and water pollution, natural resource management, and forest area impact the $LnCO_2$ levels in BRICS nations over the period from 1990 to 2023. It represents a pioneering effort in exploring the links between air and water pollution, natural resource management, and forest area within the BRICS countries, specifically focusing on load capacity factor dynamics. To achieve the research objectives, various panel methods from both first- and second-generation approaches were applied, with cross-sectional dependence incorporated into the methodology. Stationarity was assessed using the CIPS and CADF unit root tests, while the existence of long-term co-integration among variables was tested with panel co-integration techniques developed by Kao and Johansen. These methodological steps reinforced the reliability of the estimators, aligning well with environmental research literature and the unique attributes of the dataset. Additionally, the PMG-ARDL approach was employed to analyze the regressors' impact on the load capacity factor.

Overall, the findings reveal (i) evidence of cross-sectional dependence, (ii) a mix of stationary behavior across I(0) and I(1) orders in the panel data, (iii) support for a long-term relationship, and (iv) that, based on PMG-ARDL estimation, only natural resource management significantly affects $LnCO_2$ in the short term. In the long term, however, air and water pollution, natural resource management, and forest area positively contribute to improvements in $LnCO_2$ and thus to environmental sustainability. Conversely, the long-term decline in $LnCO_2$ can be linked to reductions in natural resource rents and forest area.

5.2. Policy Recommendations

To enhance economic benefits through improved environmental quality, BRICS nations should prioritize a suite of targeted policies that foster sustainable development. First, implementing stricter regulations on air and water pollution can significantly reduce health costs and boost productivity by creating cleaner living conditions. BRICS countries, which rely heavily on industrial outputs, must strengthen pollution control standards, incentivizing industries to adopt greener technologies. Subsidizing renewable energy sources and introducing financial incentives for eco-friendly infrastructure can encourage sustainable practices across sectors, reducing reliance on fossil fuels and minimizing carbon emissions.

Furthermore, effective natural resource management policies, such as sustainable logging, responsible mining practices, and reduced deforestation, are essential for preserving forest area and ensuring long-term ecological health. The establishment of environmental awareness programs can also drive community engagement in conservation efforts, fostering a culture of sustainability at both local and national levels.

To support these measures, BRICS nations should increase funding for green technological innovation and invest in research that explores the economic benefits of environmental policies. Establishing partnerships with international organizations and adopting best practices in sustainability will allow BRICS countries to align economic growth with environmental responsibility, potentially boosting economic resilience, reducing poverty, and enhancing quality of life across the region.

5.3. Limitations and Future Research Directions

This study quantifies the economic benefits of improved environmental quality in BRICS nations but faces several limitations. Firstly, the study relies on available secondary data, which may not fully capture all dimensions of environmental quality or economic benefits, particularly where data is sparse or inconsistent across BRICS countries. Additionally, the focus on aggregate indicators for environmental quality—such as CO_2 emissions—may overlook specific pollutants or localized environmental issues that affect regional economies differently. Methodologically, while panel data techniques capture general trends, they may not account for nuanced interactions between environmental and economic variables unique to each BRICS country.

Future research could address these limitations by incorporating primary data sources or more granular environmental metrics. Expanding the analysis to include variables like particulate matter, forest area loss, and water quality could offer a more comprehensive view of environmental impacts on economic growth. Moreover, exploring non-linear relationships between economic development and environmental quality, or applying machine learning methods to analyze complex interactions, could improve predictive accuracy. Comparative studies with non-BRICS emerging economies might also reveal unique drivers within BRICS nations and help tailor more effective environmental policies. Ultimately, these enhancements would refine the understanding of the economic value of sustainable environmental practices in emerging economies.

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