Energy Engineering

Tech Science Press

https://doi.org/10.32604/ee.2026.085626

ARTICLE

Modelling the Dynamics between Life Expectancy, Economic Growth, Renewable Energy Transition, and Carbon Footprints in BRICS Economies

Seyma Caliskan Cavdar[1] **and Festus Victor Bekun**[2,*]

[1]Faculty of Economics, Administrative and Social Sciences, Department of Economics, Dogus University, Istanbul, Türkiye
[2]Faculty of Economics, Administrative and Social Sciences, Istanbul Gelisim University, Istanbul, Türkiye

*Corresponding Author: Festus Victor Bekun. Email: fbekun@gelisim.edu.tr

Received: 14 May 2026; Accepted: 15 July 2026; Published: 12 November 2026

ABSTRACT: With rapid economic growth in BRICS, significant concerns about sustainability and climate change have emerged. However, changing demographics, longer lifespans, and the growing adoption of renewable energy have shifted growth's environmental impacts. Using a panel Autoregressive Distributed Lag (ARDL) approach, robust cointegration analyses establish the long-run relationship between the constructs. The ARDL panel estimates that higher economic growth (GDP) indicates greater affluence, which, along with population growth, has positive long-run effects and therefore increases CO_2 emissions. However, these effects were offset by the adverse effects of increased renewable energy consumption, which reflects technological progress, and life expectancy, which reflects demographic transition, in controlling emissions. In contrast, the causality analysis provides evidence of bidirectional causality between GDP and CO_2 emissions, suggesting a complex interaction. Furthermore, this study finds that renewable energy consumption, population growth, and life expectancy individually have unidirectional causal effects on CO_2 emissions. Robustness estimates using fully modified ordinary least squares (FMOLS) and dynamic ordinary least squares (DOLS) support the ARDL hypothesis. These results support the applicability of the Impact = Population × Affluence × Technology (IPAT) model, with proper consideration of the mutual interactions among population, affluence, and technology in determining the key drivers of ecological impact.

KEYWORDS: CO_2 emissions; economic growth; population dynamics; energy transition; IPAT model

1 Introduction

The increased emission of greenhouse gas emissions, mainly CO_2, have driven severe environmental devastation in the pursuit of sustained economic prosperity [1]. This problem specifically affects the BRICS (Brazil, Russia, India, China, and South Africa) because they collectively represent a significant share of the global population and contribute substantially to global CO_2 emissions. These economies experienced remarkable improvement and progress in the past couple of decades through the support of industrialization, urbanization, and rising prosperity [2]. Despite this rapid progress, it came at an immeasurable environmental cost, as greenhouse gas emissions in these countries have continued to rise. To fight climate change more effectively and ensure economies keep growing and developing, policies and measures must address energy use patterns, demographic indicators, economic development, and population dynamics, including CO_2 emissions patterns in the BRICS economies. As populations in BRICS countries grow, demand for products and services will increase, energy consumption will rise, and economic activity will expand. This, in turn, will produce more CO_2. This trend remains especially significant in countries like India and Brazil,

Copyright © 2027 The Authors. Published by Tech Science Press. This work is licensed under a Creative Commons Attribution 4.0 International License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

with enormous and growing populations [3,4]. Economic growth, as measured by GDP per capita, remains a significant predictor of ecological degradation [5]. Without technical innovation and government support to limit these impacts, GDP growth in BRICS states and an increasingly affluent population will likely drive greater use of products and services, higher energy consumption, and potentially more emissions [6]

Nevertheless, it will be possible to reduce population growth (PGP) and CO_2-Driven impacts on GDP through the operation of sustainable technologies, such as renewable energy (RNE) sources [7]. Brazil, with its numerous hydropower and biofuel-based initiatives, and China, one of the world's largest additions to renewable energy capacity, are examples of technical breakthroughs supporting emission restrictions [8,9]. Further, demographic indicators such as life expectancy (LEO) are closely linked to population dynamics and GDP and will help reflect CO_2 emission dynamics [5,10]. Lower fertility and population growth are generally associated with rising life expectancy [11]. This research adopts the IPAT model, which posits that ecological impact is a function of population size, economic growth (affluence), and the technology employed [12]. The study accepts the IPAT model's usefulness and timeliness and further integrates life expectancy and population dynamics into the environmental discourse in BRICS states, thereby explaining the model's comprehensiveness [13,14].

Despite many studies exploring CO_2 emissions and ecological decline, an integral understanding of the complex dynamics among PGP, GDP, RNE use patterns, and demographic transitions in the BRICS nations during a rapid rise remains far from realized. Present contributions largely focused on individual nations/groups and failed to consider the special characteristics and diversity of the BRICS bloc [15]. Further, a key weakness of these contributions is their reliance on static or linear constructs and their neglect of possible nonlinearities and interactions among the focus variables [16]. We utilize panel autoregressive distributed lag (ARDL) to overcome these gaps. This general empirical template allows consideration of linear relationships and short- and long-run varying features, useful for policy and ecological modeling in the BRICS [17,18]. The research focuses on the interrelationships among economic growth, life expectancy, renewable energy use, population growth, and carbon emissions in BRICS countries. The objectives of the paper are to: (i) examine the impact on environmental quality from both the long-run and short-run perspectives; (ii) conduct a test of the existence of a long-run equilibrium; and (iii) identify any causalities. The research questions include: (1) What is the influence of growth, life expectancy, use of renewable energy, and population growth on BRICS carbon emissions? (2) Do these variables have a long-run equilibrium?

Consequently, the panel ARDL approximation permits cointegration testing and provides an inclusive understanding of the long-run equilibrium relationship among the key indicators [19]. This research is motivated by the intractable global threat of climate change and its far-reaching consequences. As emerging-market forebears and major global CO_2 emitters, the BRICS countries play important roles in shaping the global future of environmental sustainability [2,20]. Drawing on the varied contributions of IPAT constituents and their interactions, this research seeks to provide policymakers, business executives, and environmentally self-motivated agents with empirical insights to inform sustainable development in the BRICS economies. We make notable contributions to literature with significant implications for policy-making and sustainable development concerns in BRICS and globally. First, the panel ARDL framework postulates careful and discriminating consideration of the dynamic relationships among CO_2 emissions, PGP, GDP, RNE, and LEO. Second, this research contributes to the sustainable development literature by providing country-specific insights into the drivers of CO_2 emissions across heterogeneous BRICS states. Third, by estimating the comparative impacts of drivers on emissions, this research can inform policymakers and decision-making in national and global contexts. Fourth, this research contributes to global climate action by providing a more accurate understanding of emission trends and drivers in the influential BRICS economies, supporting more targeted, root-based emissions reductions.

2 Review of Related Studies

2.1 Summary of Studies between Life Expectancy (LEO) and CO_2 Emissions

CO_2 and LEO are related, with different impacts across states and income classes. Studies show that CO_2 and LEO are inversely related in poor and middle-income states, irrespective of emission sources, and that this relationship is associated with health-harm indicators [21]. Significant LEO indicators affect health care, social protection, and international policy decision-making [22,23]. Classic LEO models conventionally considered mortality rates, but newer models aim to include more variables, such as education, health, and social protection, to achieve more precise predictions in Predicted Life Expectancy Models (PrLE) [23].

Moreover, health expenditure, the number of doctors and beds in health units, social sector expenditure, GDP level, and the prevalence of chronic diseases have been found to contribute significantly to life expectancy [24]. Consumption habits and prevalence of smoking are found to significantly determine life expectancy, and this determination remains particularly in high-income countries [11]. In Pakistan, all greenhouse gases, including CO_2, negatively affect life expectancy, while methane and nitrous oxide emissions show a significant positive association [5]. Analyses across Asia and Africa indicate that life expectancy at various quantiles is not significantly related to CO_2 emissions, and that clean energy sources contribute significantly to ecologically healthy outcomes [25]. Examinations across various regions, including Nigeria, conclude that CO_2 emissions in this nation negatively affect the scale of endogenous technical change [10]. Moreover, studies examined the contribution of various CO_2-emitting sources, such as liquid and solid fuels, to LEO and found significant negative impacts from these sources.

2.2 Summary of Studies on the Relationship between Renewable Energy Consumption (RNE) and CO_2 Emissions

Machine learning policies, such as polynomial regression, are useful for predicting future RNE expansion, and future additions are likely to average 2.61% [26]. Precise RNE prediction, with strong contributions from solar and wind, is notable given their variability; transportation RNE installations contribute positively to GDP, and GDP growth influences RNE deployment in the sector [27]. RNE is vital for lowering carbon emissions worldwide. Studies suggest that a surge in the percentage of RNE might contribute to a decline in emissions, especially in low- to middle-income countries [28–30]. Specifically, a 1% increase in RNE may lead to a 0.26% reduction in emissions, indicating RNE's influence on lowering CO_2 [31,32]. RNE contributes to ecological sustainability and possible carbon neutrality by reducing CO_2 emissions by about 0.357% to 0.428% in E7 nations [33,34]. It has also been inferred that, amid economic complexity and wealth disparity, using RNE reduces carbon emissions, promising a cleaner future [35]. In the long term, researchers used Panel ARDL models for RNE production and emissions. The models identified significant negative relationships among biofuel, hydropower, and solar energy that reduced CO_2 emissions in OECD states [36].

Other studies used the AMG estimation approach and found that RNE significantly reduces long-term carbon emissions, offering a realistic way to combat environmental deterioration in rapidly growing Asian nations [37]. With remittances and technological innovation, RNE helps lessen emissions in China [38]. Similarly, RNE may reduce carbon emissions, thereby mitigating climate change [39]. However, the link between RNE and carbon reduction differs across various economies. Furthermore, the link between RNE and carbon emissions is nonlinear, with varying thresholds affecting the rate of decline in CO_2 emissions [40]. Promoting RNE use, alongside acceptance and investment policies, will play a crucial role in achieving significant emissions reductions and combating global warming in a timely and effective way.

2.3 Summary of Studies between Population Growth (PGP) and CO_2 Emissions

The IPAT model identifies population, GDP, and the region of manufacture as drivers of CO_2 emissions [41]. Population plays a noteworthy role in driving ecological concerns, such as air pollution, in the IPAT system, which measures the impact of human activity across the biosphere [42]. Numerous studies confirm that population growth fuels energy consumption and CO_2 emissions [43]. In Nigeria, CO2 emissions and population growth show a significant correlation, highlighting the need for climate-friendly innovation to manage population-driven increases in emissions [44]. In India, population growth is escalating environmental concerns and hindering the implementation of sustainable policies in our generation [45]. Likewise, in Afghanistan, population and GDP strongly influence energy-related CO_2 emissions, with 1% increases in GDP and 0.32% increases in CO_2 observed. Declining birth rates are expected to significantly raise income per capita and reduce carbon emissions, perhaps signaling a need for population policy to mitigate global climate change [46]. Population growth, urbanization, and energy use in Pakistan contribute to CO_2 emissions, underscoring the need for cleaner energy use and population management to mitigate ecological deterioration [47]. It was also discovered that, while the link between PGP and emissions levels is noteworthy for states like India and Brazil, it is much weaker and almost insignificant for China and Indonesia when using the ARDL bounds test method from 1970 through 2012 [4].

Additionally, reports indicate that halting population growth could lower worldwide CO_2 emissions by 16%–29% by 2050, demonstrating significant potential to reduce emissions and mitigate climate change [48]. In European nations, population increase affects CO_2 emissions differently. Recent accession nations have greater-than-proportional influence, whereas veteran EU members exhibit lower, non-significant elasticities [49,50]. The IPAT model supports a global linear relation between CO_2 emissions and population growth, but variables and relations, such as technology and affluence, also contribute to emission levels [51–55]. Population decarbonization remains the cornerstone of policies to curb carbon, and broad-based measures are needed to address this relationship. Population agglomeration creates efficient industrial structures that are unacceptable in terms of carbon emissions, but the resulting geographical spillover impacts are felt in nearby areas.

2.4 Summary of Studies on the Relationship between Economic Growth (GDP) and CO_2 Emissions

A considerable body of literature has examined the complex relationship between GDP and emissions. Nevertheless, the correlation between GDP and emissions spans multiple dimensions and displays different patterns across stages of development [56]. Further economic progress is expected to raise carbon emissions, even with improved carbon regulations, because carbon prices respond only weakly to income increases [57]. In contrast, the data shows an undesirable interplay between CO_2 emissions and GDP globally over the past 50 years, suggesting that economic growth adversely affects carbon emissions [56]. Dynamic panel assessments, specifically two-step system GMM [30], uncovered an inverted U-shaped relationship between GDP and emissions in highly globalised regions, with a turning point at around 67,200 international dollars at present value, as stated by the World Bank and empirical research [45,58]. In G7 nations, carbon dioxide emissions and GDP exhibit a cyclical connection, with economic expansion fueling carbon emissions. Bidirectional causation implies that reducing emissions without impacting GDP requires rapidly implementing renewable energy sources [59].

Furthermore, fuzzy-set ideal-type analysis shows that GDP and CO_2 emissions are closely linked worldwide, contradicting the idea of decoupling and calling for effective regulatory measures to address environmental consequences [60]. Comparatively, the GDP-CO_2 emissions link differs across G-7 nations, showing M-, N-, and inverted U-shaped patterns over an extended historical period [56]. GDP's effect on emissions may follow an inverted U-shaped curve: initially, as GDP grows, emissions rise. However, further

GDP expansion can decrease emissions [56]. Additionally, a nation's urban and rural population sizes have been shown to directly affect carbon emissions, with larger populations associated with higher emissions.

3 Methodology

3.1 Data Description

In this connection, the data for the period 1990 to 2020 are adopted. In line with the research objective, the measurement data on the variables of interest-CO_2 emissions, Life expectancy (LEO), Population growth (PGP), Economic Growth (GDP), and Renewable Energy Consumption and Transition (RNE)-are sourced from the World Bank Database, WDI, 2023. This period is carefully selected because consistent data on the indicators of interest have become more accessible for BRICS economies. Table 1 below presents detailed information on the dimension and database used for each construct studied.

Table 1: Variable description.

Variable	Symbol	Details of Variables	Source
Carbon emissions	CO_2	CO_2 (metric tons per capita)	[58]
Economic Growth	GDP	Per Capita (constant 2015 US$)	[58]
Life expectancy	LEO	birth, total (years)	[58]
Renewable energy consumption	RNE	% of total final energy consumption	[58]
Population Growth	PGP	Population growth (annual %)	[58]

3.2 Trend Analysis of Variables under Consideration

Fig. 1 depicts the increase in life expectancy across all BRICS states over the past three decades. China has shown the most notable growth, rising from around 68 years in 1990 to about 77 years in 2020. Russia, which had the lowest life expectancy among BRICS countries in the late 1990s, has also made substantial progress, catching up with other countries by 2020. Brazil, India, and South Africa have seen more gradual but consistent increases in life expectancy during this period. As shown in Fig. 2 below, China's economy has grown remarkably, with its GDP per capita rising from around $300 in 1990 to over $10,000 in 2020, surpassing that of all other BRICS countries. India's economic renaissance has also been strong, but not as strong as China's. Brazil, Russia, and South Africa also experienced volatility in their economic growth rates, with both uptrends and periods of stagnation. Fig. 3 shows the trend in CO_2 emissions for the BRICS countries over the past three decades. China experienced a rapid rise in carbon emissions, from approximately 2 metric tons per capita in 1990 to more than 8 metric tons in 2020, which masks the country's rapid industrialization and economic growth.

Similarly, India experienced a significant increase in carbon emissions, though to a lesser extent than in China. These other countries observed a relatively small increase in their carbon emissions over the same period. BRICS populations varied, with India growing the fastest and Russia and Brazil declining or showing flat growth, as shown in Fig. 4. Fig. 5 presents RNE usage patterns across the BRICS nations from 1990 to 2020. Brazil has been and remains the largest user of RNE, with a major portion of its energy mix coming from hydropower and biofuels. Renewable energy use in India and China also increased sharply as they expanded their energy sources and addressed environmental concerns. Russia and South Africa saw a more modest increase in RNE over the same period.

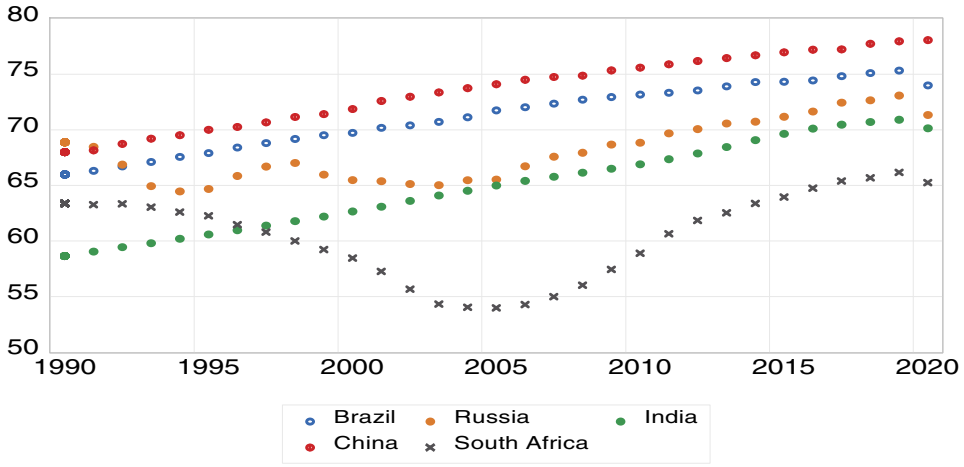


Figure 1: Life expectancy from 1990 to 2020.

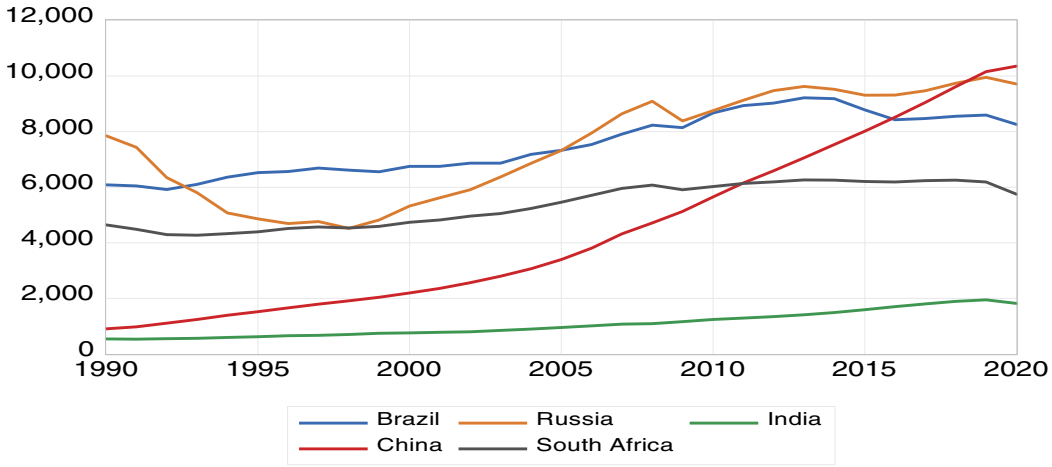


Figure 2: Economic growth from 1990 to 2020.

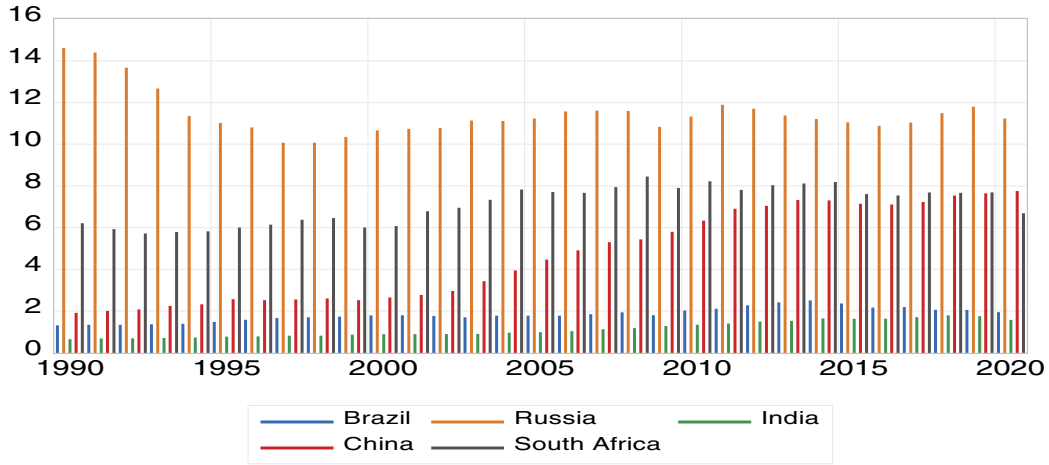


Figure 3: Carbon emissions from 1990 to 2020.

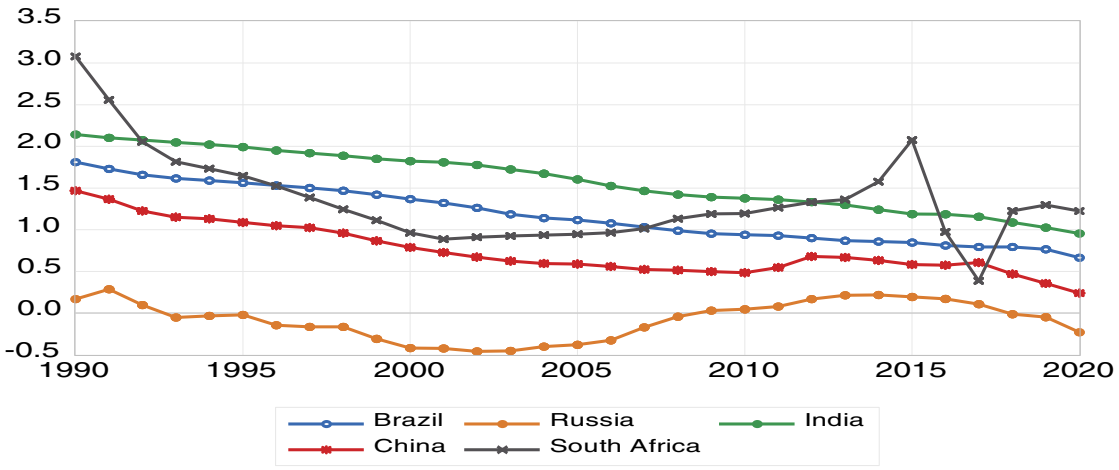


Figure 4: Population growth from 1990 to 2020.

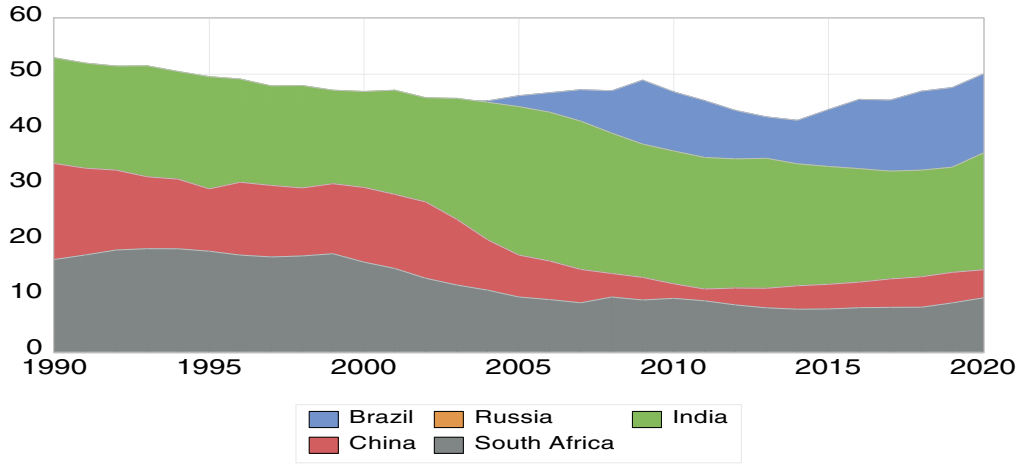


Figure 5: Renewable energy consumption from 1990 to 2020.

3.3 Theoretical Framework and Empirical Model

The IPAT (Impact = Population × Affluence × Technology) framework supports a widely accepted hypothesis for estimating ecological footprints in economics and environmental science. It argues that ecologically caused impacts from human activity, such as CO_2 emissions, are a multiplicative product of three key variables: population size, affluence, and technology use [53–55]. It advocates multiplicative interaction, showing that a factor's variation influences the environmental impact in a straightforward manner, *ceteris paribus*, relative to the other two variables. It considers population growth, economic growth, and technological progress as the primary drivers while treating other potential factors as negligible or constant. However, the model accepts a linear, proportional link among the factors and ecological impact. In this study of BRICS economies, the IPAT model aligns well with the identified variables and provides a theoretical basis for understanding their relationships with CO_2 emissions [59,60]. Population growth, represented by the variable Population growth, is expected to increase resource demand, energy use, economic activity, and CO_2 emissions.

As BRICS nations develop and citizens become more affluent, this could lead to higher consumption, energy demand, and potentially higher emissions unless technological advances or policy interventions mitigate them. The technology factor is measured by RNE to green, more RNE-based offsetting GDP and

PGP impacts. Though not a variable in IPAT, life expectancy intersects with population trend and economic improvement, significant constituents of IPAT. Improved life expectancy often accompanies reduced fertility rates, slower population growth, improved economic status, and a higher quality of life. This work advocates using the IPAT model as a common lens to explore how PGP, GDP, and technology produce environmental impact. This research in BRICS has a suitable theoretical background, as it aligns with population growth, GDP (affluence), renewable energy (technology), and life expectancy (Population- and economics-related). With these aligned variables corresponding to IPAT constituents, research can explore their respective contributions to CO_2 emissions and guide policies that facilitate sustainable improvement and manage environmentally related outcomes in BRICS economies. This is why the research template uses the Stochastic Impacts of Regression on Population, Affluence, and Technology (STIRPAT). The IPAT ecological footprint (population, affluence, and technology) was widely used in the literature to examine the contribution of anthropogenic activity to ecological quality [12]. This multiplicative specification of the IPAT identity can be written as

$$I = PAT \tag{1}$$

The model assumes ecological impacts (I) are a function of technology (T), population (P), and proxies for economic variables or wealth (A), often proxied by GDP. To address the consequences and limitations of the IPAT model, we propose a stochastic STIRPAT (Stochastic Impacts by Regression on Population, Affluence, and Technology) approach. The underlying system of the STIRPAT model is the following:

$$I_i = aP_i^{\beta} A_i^{\gamma} T_i^{\delta} \varepsilon_i \tag{2}$$

The logarithmic form of Eq. (2) is expressed as follows:

$$\log I_i = a + \gamma \log A_i + \beta \log P_i + \delta \log T_i + \varepsilon_i \tag{3}$$

The STIRPAT model offers flexibility in accommodating different features that drive ecological degradation. This background was successful in accommodating appropriate variables such as mechanical changes, urbanization, energy mixes, income inequality. Consequently, environmental impact (I) by CO_2 emissions, population (P) by population growth, affluence (A) by GDP, and technology (T) by RNE. Built on the empirical foundations that have been studied, the following statement is stated at time, denoted as t:

$$CO2_t = \mathfrak{f}(GDP_t, LEO_t, RNE_t, PGP_t) \tag{4}$$

$CO2_t, GDP_t$, LEO_t, RNE_t and PGP_t are the CO_2 emissions, economic growth, life expectancy, renewable energy consumption, and population growth at time t. However, we adopted log-linear specifications because they have been empirically shown to provide reliable evidence on carbon emissions and climate change dynamics across independent and dependent factors. The following equation specifies the econometric model that presents the empirical formulation of the CO_2 function.

$$\ln CO2_t = \beta_0 + \beta_1 \ln GDP_t + \beta_2 \ln LEO_t + \beta_3 \ln RNE_t + \beta_4 \ln PGP_t + \varepsilon_t \tag{5}$$

3.4 Methodology Sequence and Rationale

This study uses a comprehensive method to evaluate the interrelationship among GDP, LEO, RNE, and PGP on CO_2 emissions in BRICS nations. First, descriptive statistics and correlation analysis provide initial insight into data distribution and associations among constructs, helping identify potential normality, skewness, and mean distributions. Next, the cross-section dependence (CD) test assesses interdependencies

among countries to ensure appropriate panel estimation [61]. Second-generation unit root tests test the stationary properties of indicators under the CD assumption, namely the CIPS unit root test. Further, Pedroni and Johansen-Fisher Cointegration tests were used to examine long-run equilibrium relationships among the variables and determine whether a stable long-term link exists among the indicators. The Pedroni test allows for heterogeneous adjustments and is further supported and checkable through the Engle-Granger cointegration test for pairwise investigations [62]. In contrast, the Johansen-Fisher test pools individual Johansen test statistics across panel members, thus affording a comprehensive approach to assessing long-run equilibrium relationships. Panel ARDL is recommended for estimating long- and short-term adjustments using the cointegration test. Using ARDL settings that allow parameter heterogeneity in long-run adjustments while assuming parameter homogeneity in the long-run relationship, we used the Pooled Mean Group (PMG) estimator. To ensure the validity of the results, we also used the Fully Modified Ordinary Least Squares (FMOLS) and Dynamic Ordinary Least Squares (DOLS) estimators. They are robust to endogeneity and serial correlation in the regressed variables because they provide efficient, consistent long-run parameter estimates. Meanwhile, DOLS remains effective by incorporating lags and leads of first-differenced, regressed variables to correct endogeneity and autocorrelation. These robustness checks help refine findings during result verification. Finally, causality tests are run to assess the direction of causality [63]. This test is critical, as it helps confirm whether variables change in relation to CO_2 emissions or whether the association is bidirectional. Fig. 6 presents the analytical flowchart outlining the methodological progression. Hence, the methodological framework rigorously and reliably assesses the dynamic interactions among GDP, PGP, RNE, LEO, and CO_2 emissions in BRICS economies.

3.5 CD Test

Given the connected activities, the study assumes a likely relationship between the data for the observed countries and their dynamism, trade, and related activities. We therefore calculated the bias-corrected LM test below

$$y_{it} = a_i + \beta_{,1} \mathrm{X}_{it} + \mu_i \; for \; i = 1, 2, 3 \ldots . N; t = 1, 2, T \tag{6}$$

X_{it} and β are estimators as $Kx1$ vectors, through time element, α_i. Those crosswise cross-sections and crosswise units of time are evenly spread, and μit spreads and that μit and they are related and included in the null evidence [64].

CD statistics have a zero true mean when cross-sectional units (N) and duration length (T) are set to some values, compared with the Lagrange Multiplier (LM) figures. An extended version of Eq. (6) to handle conditions of unbalanced panel data.

$$CD = \sqrt{\frac{2T}{N\,(N-1)}} \left(\sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \sqrt{\mathrm{T}_{ij}} p_{ij} \right) \tag{7}$$

whereas $\mathrm{T}_{ij} = \#\,(\mathrm{T}_i \cap \mathrm{T}_j)$

$$\hat{\rho} ij = \hat{\rho} ij = \frac{\sum_t \epsilon \, \mathrm{T}_i \cap \mathrm{T}_j (\hat{u}it - \hat{u}i)(\hat{u}jj - \hat{u}j)}{\{\sum_t \epsilon \, \mathrm{T}_i \cap (\hat{u}it - \hat{u}i)^2\} 1/2 \{\sum_t \epsilon \, \mathrm{T}_i \cap \mathrm{T}_i \, (\hat{u}it\hat{u}jj)^2\} \, SS \, 1/2} \tag{8}$$

and

$$\hat{u}i = \frac{\sum_t \epsilon \, \mathrm{T}_i \cap \mathrm{T}_j, \hat{u}it}{\#(\mathrm{T}_i \cap \mathrm{T}_j)} \tag{9}$$



Figure 6: Analytical flow chart.

3.6 CIPS Unit Test

When CD exists, standard panel stationarity unit root tests become pointless; this issue is handled by adjusting the classic ADF technique, integrating cross-sectional mean changes of lagged terms, and reforming one of the module edifices, resulting in an original panel unit root calculation that accounts for both CD and heterogeneity. The CIPS stationarity test is based on the regular individual CADF tests for the whole group. This designates the CIPS test.

$$CIPS\,(N,T) = \frac{1}{N}\sum_{i=1}^{N} t_i\,(N,T) \tag{10}$$

3.7 Cointegration Estimation

The Pedroni cointegration examination is based on a cointegrating regression model. It examines the long-run symmetry link among the dependent variable and multiple explanatory factors, permitting individual-specific constants [62]. The cointegration equation is provided.

$$y_{it} = \beta_i t + \beta_{1it} x_{1it} + \beta_{2it} x_{2it} + \ldots + \beta_{kit} x_{kit} + \epsilon_{it} \tag{11}$$

y_{it} captures the endogenous variable of individual I at time t, $\beta_i t$ represents the intercept term of the individual-specific intercept term, β_{1it}, β_{2it}, and β_{kit} represent the individual-specific slope coefficients of the respective explanatory variables x_{1it}, x_{2it}, and x_{kit} are regressors of the individual i at time t, and ϵ_{it} represents the error term. The Johansen-Fisher test is used in the vector autoregressive (VAR) formulation in first differences. This relates the first difference in a vector of non-stationary variables to their lagged variables, their first-difference lags, and the error term.

$$y_{it} = a_i + A_1 y_{it-1} + \ldots + A_q y_{it-q} + \omega_{it} \tag{12}$$

$$\Delta y_{it} = a_i + \prod y_{it-1} + \sum_{j=1}^{\rho} \Gamma_i \Delta y_{it-j} + \omega_{it} \tag{13}$$

Johansen test is based on a vector autoregressive (VAR) in first differences model where the vector of variables' non-stationarity variation change (Δy_{it-j}), assumed to be explained in terms of its lagged levels (y_{it-1}), lagged first differences (Δy_{it-j}), and an error term (ω_{it}).

3.8 Main Model Estimation-Panel ARDL

The study employs the ARDL to identify long- and short-run correlations among the constructs. This approach estimates both short-run and long-run dynamics. The PMG within the ARDL setting allows heterogeneity in short-run adjustment parameters while assuming homogeneity in the long-run relationship. In Eq. (14), the research considers that GDP, LEO, RNE, and PGP can contribute to CO_2 emissions. Including these variables and CO_2 emissions in the relations will help detect the influences of environmental destruction in BRICS countries. Previous studies indicate that these variables contribute significantly to climate change.

Eq. (14) implies that GDP, life expectancy, renewable energy use, and population growth may significantly affect CO_2 emissions. Factors such as healthcare expenditure, physician and hospital bed density, social spending, GDP level, and prevalence of chronic diseases play crucial roles in determining LEO [59]. India's growing population exacerbates environmental pressures and hinders sustainable development efforts [45]. Similarly, in Afghanistan, population and GDP are closely linked to emissions, with a 1% rise in PGP resulting in a 0.32% gain in CO_2 levels. RNE, transmission, and innovation help lower China's carbon footprint, as the study's empirical analysis shows [38]. Utilising renewable energy sources may minimise carbon emissions, which could help slow climate change [39]. However, the link between RNE and carbon reduction differs among diverse economies. Furthermore, the link between RNE and CO_2 emissions is nonlinear, with shifting thresholds affecting the rate of carbon-emission reduction [40]. The specifications of the Panel ARDL model lags were selected using the AIC criterion. Of all possible choices, the ARDL (1, 4, 4, 4, 4) specification had the lowest AIC value and was therefore used for estimation.

$$\Delta \ln CO2_{it} = \alpha + \gamma_1 \ln CO2_{it-1} + \gamma_2 \ln GDP_{it-1} + \gamma_3 \ln LEO_{it-1} + \gamma_4 \ln RNE_{it-1} + \gamma_5 \ln PGP_{it-1} + \sum_{i=1}^{\rho} \varnothing_i \Delta \ln CO2_{it-i} + \sum_{i=1}^{\delta} \varphi_i \Delta \ln GDP_{it-i} + \sum_{i=1}^{\sigma} \beta_i \Delta \ln LEO_{it-i} + \sum_{i=1}^{\varrho} \psi_i \Delta \ln RNE_{it-i} + \sum_{i=1}^{\varpi} \vartheta_i \Delta \ln PGP_{it-i} + \varepsilon_{it} \quad (14)$$

The long-term constants are γ_1, γ_2, γ_3, γ_4, and γ_5. Where the short-run constants in the equation are, φ_i, β_i, ψ_i, ϵ_i and ϑ_i. The operator Δ guides the first difference of the constructs. If cointegration is noticed within the ARDL model (Eq. (14)), the error correction model can be uttered as Eq. (15). Error correction (ECT) for Eq. (14) is specified in Eq. (15).

$$\Delta \ln CO2_{it} = \alpha + \sum_{i=1}^{\rho} \varnothing_i \Delta \ln CO2_{it-i} + \sum_{i=1}^{\delta} \varphi_i \Delta \ln GDP_{it-i} + \sum_{i=1}^{\sigma} \beta_i \Delta \ln LEO_{it-i} + \sum_{i=1}^{\varrho} \psi_i \Delta \ln RNE_{it-i} + \sum_{i=1}^{\varpi} \vartheta_i \Delta \ln PGP_{it-i} + \varphi ECT_{it-1} + \mu_{it} \quad (15)$$

ECT_{it-1} embodies a one-period lag of the ECT, where φ connote the speed of adjustment from short-run dynamics.

3.9 Robustness Checks

The study further proceeds to support and validate the reliability of the primary Panel ARDL model with the dynamic ordinary least squares (DOLS) and the fully modified ordinary least squares (FMOLS); this attempt seeks to confirm the robustness of the findings from the baseline model, thus providing further empirical and strong support to the conclusions.

3.10 Causality Assessment

This method calculates the average individual Wald assessment shown for each cross-sectional unit [63]. In their panel causality test, follow the computations outlined below:

$$y_{it} = a_i + \sum_{k=1}^{k} y_i^{(k)} y_{it-k} + \sum_{k=1}^{k} \beta_i^{(k)} x_{it-k} + \varepsilon_{it} \quad (16)$$

$$W_{N,T}^{Hnc} = \frac{1}{N} + \sum_{i=1}^{N} W_{it} \quad (17)$$

In this case, $ZHnc\,N, T$ signifies the z-statistic, where N is the sum of cross-sections and K is the optimum lag length.

4 Results and Discussion

Table 2 presents descriptive statistics and correlation matrices for the constructs investigated, intended to reveal correlations between PGP, LEO, GDP, and RNE and CO_2 emissions in the BRICS countries. The descriptive statistics include the mean, median, maximum, minimum, standard deviation, skewness, kurtosis, Jarque-Bera measure, and correlation possibility values for each index. These statistics reveal the central tendency, variability, and distribution of the variables. The correlation results show the pairwise correlation coefficients between the constructs.

Table 2: Descriptive statistics and correlation matrix.

	$lnCO_2$	lnGDP	lnLEO	lnRNE	lnPGP
Mean	1.294	8.278	4.210	2.850	0.958
Median	1.496	8.656	4.219	2.922	1.014
Maximum	2.682	9.245	4.357	3.969	3.078
Minimum	−0.434	6.270	3.988	1.156	−0.460
Std.Dev	0.914	0.861	0.086	0.974	0.692
Skewness	−0.191	−0.962	−0.550	−0.536	−0.093
Kurtosis	1.633	2.572	2.829	1.852	2.732
Jarque-Bera	13.008	25.129	8.013	15.922	0.691
Probability	0.002	0.000	0.018	0.000	0.707
Sum	200.635	1283.220	652.658	441.798	148.541
Sum Sq. Dev	128.669	114.275	1.143	146.117	73.813
Observation	155	155	155	155	155
Correlation matrix					
$lnCO_2$	1.000				
lnGDP	0.685	1.000			
lnLEO	0.006	0.326	1.000		
lnRNE	−0.927	−0.509	−0.068	1.000	
lnPGP	−0.699	−0.547	−0.368	0.737	1.000

The variables show varying dispersion around their means, with CO_2 emissions and renewable energy use having substantially larger standard deviations than their means, suggesting greater heterogeneity among the BRICS nations. The skewness values show that most variables are somewhat undesirably skewed, except CO_2 emissions, which have a very modest positive skewness. The kurtosis values imply that the variables' distributions are generally flatter than a normal distribution, except for GDP per capita, which is somewhat leptokurtic. According to the Jarque-Bera test statistics, most variables are not normally distributed, except population growth, which does not reject the null hypothesis of normality at the 5% significance level. The strong negative correlation (−0.927) between CO_2 emissions and RNE consumption suggests that transitioning to RNE sources will help reduce carbon emissions. Nations with advanced RNE use tend to have lower CO_2 emissions. The negative link between CO_2 emissions per capita and PGP (−0.699) implies that nations with higher PGP rates may have lower emissions, likely due to lower GDP or RNE consumption. The positive link between GDP and LEO (0.326) aligns with the common finding that economic expansion is linked to better healthcare, living conditions, and longer life expectancy. The negative connection between life expectancy and population growth (−0.368) agrees with the demographic transition hypothesis, showing that population growth rates tend to drop as life expectancy rises. These findings provide essential information about the links and inform the future panel ARDL analysis, which explores the dynamic and causal linkages while accounting for possible endogeneity and cross-sectional dependency across the BRICS nations.

4.1 Stationarity Check

Table 3 presents the CIPS unit root test results, which are significant for assessing the stationarity characteristics of the panel data parameters used in the panel estimation. CIPS testing improves upon IPS unit root testing in panel units by pooling cross-sectional interdependencies in aggregate. Given the likelihood of interdependencies due to their integrated economic and geopolitical connections, this feature is unique

to the BRICS nations. We assume two situations: one with and one without a constant and trend term in the underlying panel unit root tests. CIPS testing assumes that all panel units have a unit root (non-stationary) in its null hypothesis. Meanwhile, the alternative hypothesis assumes that more than one panel unit is stationary.

Table 3: CIPS unit root assessment.

Variable	Level	Constant	Constant and Trend
$lnCO_2$	0	−4.058***	−3.742***
lnGDP	0	−3.707***	−3.797***
lnLEO	0	−1.419	−2.231
	1	−2.448**	−2.921**
lnRNE	0	−3.008***	−3.710***
lnPGP	0	−1.865	−2.443
	1	−2.732***	−2.942***

Note: ***: 1%, **: 5% level of significance, respectively.

CO_2 emissions ($lnCO_2$) and lnGDP remain stationary at existing levels, with a constant trend. These constructs do not have a unit root issue, and we may utilize their level values in the ensuing analysis. Life expectancy (lnLEO) seems non-stationary at its level and has a constant term. However, the first difference (denoted by 1) is stationary. The first difference of lnLEO is stationary, showing that it is an I (1) construct (integrated of order 1). Renewable energy consumption (lnRNE) is stationary at its level, with a constant and a constant trend comparable to $lnCO_2$ and lnGDP. Population growth (lnPGP) is non-stationary at its level, with persistent and constant trend components. After taking the first difference, the variable becomes stationary, suggesting it is I (1). These outcomes are relevant for the upcoming panel ARDL analysis. The ARDL method permits the integration of I (0) and I (1) variables but not I (2) or higher-order integrated variables. Since all the constructs in this research are I (0) or I (1), the ARDL method is appropriate for evaluating the long-run and short-run links among the constructs. The CIPS test outcomes confirm that the variables are well-behaved and do not exhibit explosive behaviour, which could lead to spurious regressions and incorrect conclusions. By addressing the stationarity issue, the analysis can proceed safely with panel ARDL and derive meaningful insights into the intricate interplay among CO_2 emissions, PGP, LEO, GDP, and RNE in the BRICS states.

4.2 CD Assessment

The results of the CD test, which is an important stage in panel data research, are in Tables 4 and 5. Classical panel data modelling assumes cross-sectional units are independent of each other (BRICS nations). In practice, this assumption often fails, particularly for heavily intertwined economies that are likely to share common global policies/shocks. There are three tests that are utilized to detect CD. Each test assumes that the null hypothesis includes cross-sections that are independent; rejecting the null hypothesis will thus denote cross-sectional dependence

Table 4 outlines that the Breusch-Pagan LM assessment yields a statistic of 189.612, indicating high significance at the 1% level (denoted by ***). This result strongly rejects the null hypothesis of cross-sectional independence, underscoring the cross-sectional interdependence between the BRICS economies. Similarly, the scaled LM test yields a statistic of 40.162, which is also significant at the 1% level, further confirming cross-sectional dependence. Furthermore, the Pesaran CD test yields −3.151, again significant at the 1% level, providing additional evidence of cross-sectional dependence across the panel units. All three assessments

uniformly reject the null hypothesis of cross-sectional independence, highlighting the interconnectedness among the BRICS economies.

Table 4: Cross-sectional dependence assessment (overall).

Test	Statistic	d.f	Prob.
Breusch-Pagan LM	189.612***	10	0.000
Pesaran Scaled LM	40.162***		0.000
Pesaran CD	−3.151***		0.000

Note: ***: 1%, level of significance.

Table 5: Cross-sectional dependence assessment using the variables.

Test	$lnCO_2$	lnGDP	lnLEO	lnRNE	lnPGP
	Prob.	Prob.	Prob.	Prob.	Prob.
Breusch-Pagan LM	0.000	0.000	0.000	0.000	0.000
Pesaran Scaled LM	0.000	0.000	0.000	0.000	0.000
Pesaran CD	0.000	0.000	0.000	0.000	0.000

In Table 5, all three test statistics have a probability value of 0.000, indicating strong significance at any conventional level. This strongly rejects the null hypothesis of cross-sectional independence for CO_2 emissions per capita, indicating cross-sectional dependence across the BRICS nations for this variable. Similarly, for $lnCO_2$, the probability values for all three tests are 0.000, demonstrating substantial evidence of CD in CO_2 emissions per capita across the BRICS states. Moreover, the probability values for life expectancy at birth are 0.000 for all three tests, demonstrating cross-sectional dependence across the BRICS nations for this metric. These results are consistent with the previous variables, as all three tests reject the null hypothesis of cross-sectional independence at the highest substantial level. The interconnections among BRICS nations indicate that policy in one country could trigger spillover effects on others in emissions reduction and GDP. Thus, local cooperation and coordinated policies that address shared challenges further strengthen the efforts of individual states' nonprofits and their purpose of developing sustainable economies.

4.3 Johansen Fisher Panel Cointegration

To examine enduring equilibrium relationships among CO_2 emissions, GDP, PGP, LEO, and RNE in the BRICS nations, we must address cointegration. To realise this aim, we use the Johansen Fisher Panel Cointegration test, which amalgamates individual cross-section cointegration assessments to derive panel-level test statistic. As presented in Table 6, the findings reveal cointegrating connections among the variables under investigation. Specifically, the Trace and Max Eigen assessment outcomes refute the null hypothesis of no cointegration at the 1% significance level. Moreover, the Trace test supports at least three cointegrating vectors, whereas the Max Eigen assessment indicates at least two cointegrating vectors at the 5% significance level. Cointegration means that although the variables deviate from long-run equilibrium in the near term, they share a static long-run equilibrium and ultimately move toward it. So whatever divergence from this equilibrium surfaces will, in the long term, be adjusted through movement in the variables.

The Johansen-Fisher test findings indicate cointegration, implying a long-run equilibrium connection among the examined indicators. This long-run convergence significantly influences policies in climate

change mitigation and green ecological transformation. While near-term variations may emerge, this underlying equilibrium relationship will ultimately establish the long-run trend [27,51].

Table 6: Johansen Fisher cointegration.

Coint. Rank	Trace Test	Prob.	Max Eigen Test	Prob.
None	123***	0.000	80.53***	0.000
At most 1	57.80***	0.000	33.21***	0.000
At most 2	33.22***	0.000	18.83**	0.043
At most 3	23.56***	0.009	13.12	0.217
At most 4	32.51***	0.192	32.51***	0.000

Note: ***: 1%, **: 5%, level of significance respectively.

Additionally, cointegration indicates mutual dependency across different factors, and integrated policy measures are required [51]. Emission reductions and renewable energy cannot be considered in isolation but must account for population and economic growth issues [33]. Additionally, cointegration supports the panel ARDL approach, which enables estimation of long-run cointegrating interactions and short-run trends [28]. This takes significant consideration of the mix of I (0) and I (1) variables that are found to be true through the CIPS unit root test.

4.4 Pedroni (Engle-Granger) Cointegration

Table 7 below lists Pedroni (Engle-Granger) Panel Cointegration test statistics, proposing an alternative methodology to test long-run equilibrium linkage among variables of concern. This test specifically examines cointegration in panels with respect to within-and between-dimensional (group statistics) and panel statistics constituents. The table presents seven test statistics: four panel statistics (v-statistic, rho-statistic, PP-statistic, and ADF-statistic) and three group statistics (rho-statistic, PP-statistic, and ADF-statistic). These statistics facilitate comparison and contrast between the null hypothesis that no cointegration prevails and the alternative hypothesis that cointegration prevails. Findings in this research show that two of the four panel statistics (the PP statistic and the ADF statistic) reject the null hypothesis of no cointegration at the 5% and 1% significance levels, respectively. These PP and ADF statistics, two of the three group statistics, reject the null hypothesis of no cointegration at the 1% significance level.

Table 7: Pedroni (Engle-Granger) cointegration.

	t-Statistic	Prob.
Within dimension		
Panel v-statistic	−0.258	0.601
Panel rho-statistic	−0.081	0.467
Panel PP-statistic	−2.238**	0.000
Panel ADF-statistic	−2.475***	0.007
Between dimension		
Group rho-statistic	1.451	0.926
Group PP-statistic	−2.490***	0.006
Group ADF-statistic	−2.372***	0.008

Note: *** shows1%, level of significance.

These findings complement the Johansen Fisher Panel Cointegration test and further confirm long-run equilibrium relationships among the constructs under study: CO_2 releases, GDP, PGP, LEO, and RNE in the BRICS nations. Multiple cointegration tests confirm that these indicators share a stable long-run relationship and that deviations from this equilibrium are temporary [28]. These findings are relevant to policymakers and stakeholders in the BRICS nations as they manage this complex web of population dynamics, GDP, and environmental sustainability. Attempts to develop RNE usage, minimise CO_2 releases, or stimulate GDP cannot be conceptualised in isolation. Instead, they must be examined within the broader dynamics of population dynamics and overall sustainability goals. Moreover, confirming cointegration makes long-run forecasting and scenario analysis possible with credible research and policymaking applications [39].

4.5 Panel ARDL Outcomes

The Panel ARDL model is reported in Table 8. The adverse and statistically significant error correction term ECT (−1) shows a long-run equilibrium association among the constructs, suggesting that deviations from this equilibrium are corrected at 17.8% per year. In the long run, GDP positively and statistically significantly influences CO_2 emissions, indicating that faster GDP growth increases CO_2 emissions over the long term. Conversely, life expectancy (lnLEO) has an adverse and significant effect on emissions, indicating that increases in life expectancy are associated with lower CO_2 emissions in the long term [11].

Table 8: Panel ARDL outcomes.

Long-Run (Pooled) Coefficients	Coefficient	Std. Error	*t*-Statistic	Prob.
lnGDP	1.313***	0.213	6.172	0.000
lnLEO	−2.807***	1.039	−2.700	0.000
lnRNE	−0.363*	0.187	−1.938	0.057
lnPGP	0.351**	0.148	2.366	0.021
Short-Run (Mean-Group) Coefficients				
ECT (−1)	−0.178**	0.007	−2.294	0.025
ΔlnGDP	0.381**	0.185	2.056	0.044
ΔlnGDP (−1)	0.220	0.299	0.469	0.465
ΔlnGDP (−2)	0.344	0.219	1.568	0.122
ΔlnGDP (−3)	0.242***	0.056	4.299	0.000
ΔlnLEO	1.146	1.528	0.750	0.456
ΔlnLEO (−1)	1.743	1.659	1.050	0.297
ΔlnLEO (−2)	1.538	2.442	0.629	0.531
ΔlnLEO (−3)	−2.082	4.033	−0.516	0.608
ΔlnRNE	−0.590**	0.235	−2.50	0.015
ΔlnRNE (−1)	−0.044	0.131	−0.342	0.733
ΔlnRNE (−2)	0.188	0.031	1.144	0.257
ΔlnRNE (−3)	−0.121	0.193	−0.632	0.531
ΔlnPGP	−0.198**	0.078	−2.515	0.015
ΔlnPGP (−1)	0.153	0.210	0.738	0.138
ΔlnPGP (−2)	−0.030	0.203	−0.149	0.682
ΔlnPGP (−3)	0.076	0.224	0.338	0.955
Constant	0.533*	0.282	1.885	0.064

Note: ***: 1%, **: 5%, *: 10% level of significance respectively. AIC (1, 4, 4, 4, 4).

Additionally, renewable energy consumption (lnRNE) has an adverse and substantial effect, demonstrating that greater utilization of RNE sources corresponds with reduced emissions over the long term [30,31]. Meanwhile, population growth (lnPGP) has a positive and substantial effect, showing that rapid population growth increases emissions in the long run [44]. The short-run coefficients indicate how variables adjust toward the long-run equilibrium. GDP has a favourable, substantial short-run effect on emissions, with the effect divided over several delays. RNE use has a negative, significant short-run outcome, whereas PGP has a negative, substantial short-run influence on emissions. Long-run coefficients give insights into sustainable development routes for BRICS. While economic growth correlates with growing emissions, the adverse consequences of renewable energy and life expectancy gains suggest that strengthening renewable sources and enhancing living standards might minimize environmental repercussions [30]. The positive GDP-emissions correlation fits IPAT's view that higher prosperity increases ecological damage.

However, the negative effects of RNE (a cleaner-technology proxy) and life expectancy (which influences population and wealth) suggest that technical and social reforms may mitigate growth's environmental impact [48]. This emphasises BRICS' potential for long-run sustainability via renewable energy, excellent living standards, and cleaner technology. The IPAT model highlights population, affluence, and technology as the main drivers of environmental impact. The Panel ARDL findings highlight interconnected strategies for economic development, population, and energy transition. Policymakers may employ these results to support sustainable economic growth while avoiding environmental implications, such as investing in renewable energy, enacting population restrictions, and incentivising cleaner technology. The short-run coefficients reflect dynamic changes toward the long-run equilibrium, highlighting the interaction among population, wealth, and technology over time. These insights may inform short-term policy decisions and help manage the transition toward sustainable pathways by accounting for the transitory implications of changes in population, economic development, and energy patterns. The substantial error correction term supports a long-run equilibrium relationship, showing that BRICS economies converge toward a sustainable equilibrium that balances environmental impact with economic growth, population dynamics, and technological improvement. This convergence aligns with IPAT's idea that population, prosperity, and technological components ultimately find a steady-state equilibrium, assuring long-term sustainability.

4.6 Robustness Estimation

Table 9 presents robustness estimation results using FMOLS and DOLS to examine the relationship between economic indicators and emissions, with CO_2 as the dependent variable. Both methods show that LNGDP has a robust positive effect on CO_2 emissions, with coefficients of 2.612 and 2.578, indicating that higher economic activity, as represented by GDP, is associated with increased CO_2 emissions. Conversely, LEO has an adverse link with CO_2 emissions, with coefficients of −0.136 and −0.144, suggesting that as energy output increases, CO_2 emissions decrease, potentially reflecting a shift towards more efficient or cleaner energy sources. The variable for renewable energy usage (RNE) displays a weak adverse link with CO_2 emissions in FMOLS, with a coefficient of −0.051, suggesting a slight reduction in CO_2 emissions associated with renewable energy use. This mixed result may indicate that renewable energy adoption has not yet reached a level that significantly reduces emissions. In contrast, PNG does not considerably affect CO_2 emissions in either model, with coefficients of 0.294 in FMOLS and 0.059 in DOLS. This suggests that PNG does not directly influence CO_2 emissions in this setting. The results emphasize the role of GDP and energy efficiency in controlling emissions, while renewable energy and PNG show limited effects.

Table 9: Robustness estimation.

Variable	FMOLS			DOLS		
	Coefficient	Std. Error	*p*-Value	Coefficient	Std. Error	*p*-Value
LGGDP	2.612***	0.418	0.000	2.578***	0.389	0.000
LEO	−0.136***	0.032	0.000	−0.144***	0.036	0.000
RNE	−0.051*	0.028	0.074	−0.032	0.030	0.290
PGP	0.294	0.276	0.288	0.059	0.303	0.845

Note: ***: 1%, *: 10% level of significance respectively.

4.7 D-H Causality Test

Table 10 presents the results of the causality test used to identify the causal connectivity between the constructs under consideration: GDP, LEO, RNE, PGP, and CO_2 emissions. In causality testing, this evaluation is a widely used approach for testing causality in panel data samples [63]. It tests the hypothesis that no constant causal effects exist and that no causality exists within any cross-sectional unit (here, the BRICS nations) and finds that the null hypothesis of no constant causal effects cannot be falsified in this test. If the null hypothesis remains unfalsified, a causal relationship exists in at least one cross-sectional unit. The table presents the test statistics (W-Stat) and respective probabilities (Prob.), along with the inference that the null hypothesis is not accepted/rejected.

Table 10: Causality test.

Null Hypothesis	W-Stat	Prob.	Conclusion
lnGDP ≠> $lnCO_2$	4.491	0.031	Rejected
$lnCO_2$ ≠> lnGDP	7.975	0.000	Rejected
lnLEO ≠> $lnCO_2$	3.949	0.098	Rejected
$lnCO_2$ ≠> lnLEO	3.852	0.118	Not Rejected
lnRNE ≠> $lnCO_2$	7.979	0.000	Rejected
$lnCO_2$ ≠> lnRNE	2.245	0.952	Not Rejected
lnPGP ≠> $lnCO_2$	4.243	0.053	Rejected
$lnCO_2$ ≠> lnPGP	0.884	0.224	Not Rejected
lnLEO ≠> lnGDP	5.670	0.001	Rejected
lnGDP ≠> lnLEO	2.223	0.968	Not Rejected
lnRNE ≠> lnGDP	8.134	0.000	Rejected
lnGDP ≠> lnRNE	2.747	0.596	Not Rejected
lnPGP ≠> lnGDP	2.234	0.960	Not Rejected
lnGDP ≠> lnPGP	3.373	0.265	Not Rejected
lnRNE ≠> lnLEO	2.373	0.857	Not Rejected
lnLEO ≠> lnRNE	2.688	0.635	Not Rejected
lnPGP ≠> lnLEO	1.678	0.637	Not Rejected
lnLEO ≠> lnPGP	6.496	0.000	Rejected
lnPGP ≠> lnRNE	2.312	0.903	Not Rejected
lnRNE ≠> lnPGP	2.360	0.867	Not Rejected

Note: does not homogeneously cause equals ≠>.

The research provides evidence of bidirectional causation between GDP and CO_2 emissions across BRICS, suggesting a reciprocal link in which economic growth and CO_2 emissions affect each other. Furthermore, it shows that LEO and RNE usage have a unidirectional causal impact on CO_2 emissions, whereas the reverse is not evident. Similarly, population growth has a unidirectional effect on CO_2 emissions, but the reverse link does not hold. The one-way link between CO_2 emissions and population growth in BRICS countries underscores the need for policies aligned with demographic trends and environmental sustainability. Policymakers should address population growth through urban planning, education, and family planning, alongside carbon-efficient technologies and renewable energy. Diversifying green industries will also help decouple growth and emissions. These findings suggest that policies should balance green dimensions and sustainable development through research. In addition, life expectancy shows a unidirectional causal effect on GDP, but not the reverse. Likewise, renewable energy use shows a unidirectional causal relationship with GDP.

Additionally, life expectancy posits a unidirectional causal influence on population growth, with no causal influence in the opposite direction. The mutual relationship between GDP and emissions signals the strength of the GDP-environment nexus in the BRICS countries, which must be understood in charting policies for sustainable GDP growth [41]. Policymakers must understand this relationship when charting policies to sustainably boost GDP. Unidirectional causal functions, as seen in the examples of LEO, RNE, and PGP in CO_2 emissions, inform policies on these variables and decisions regarding CO_2 emissions. Assigning RNE and composing population policies can reduce emissions [32]. Unidirectional causality between life expectancy and GDP per capita suggests that GDP growth will be driven by improvements in living standards and health infrastructure. Similarly, the unidirectional causality between RNE and GDP indicates that energy transitions toward green energy will enable GDP growth [31].

5 Conclusion

The research empirically confirms the linkages between CO_2 emissions and GDP, LEO, PGP, and RNE across the BRICS nations. The findings align with the IPAT model, pointing to population, affluence, and technology as the main ecological drivers. First, the long-term positive association between GDP (a proxy for affluence) and CO_2 emissions supports the IPAT model's forecast that additional affluence will amplify ecological impact. Offsetting forces from employment in renewable energy (a proxy for clean technology) and improvements in life expectancy (through population dynamics and affluence) suggest that technological and societal progress can offset the ecological outcomes of GDP. Second, the bidirectional causation between GDP and CO_2 emissions indicates a complex interaction between economic growth and ecological outcomes and supports complementary policies that balance ecological preservation and economic growth, in line with the IPAT model. Third, the unilateral causal contributions of RNE, PGP, and LEO to CO_2 emissions imply that policies targeting these variables can directly influence CO_2 emissions in the BRICS countries. This helps identify the IPAT model's population, technology, and socio-economic variables driving the environmental issue. Moreover, the convergence and correlation of the constructs, through the significant error-correcting term, support the hypothesis that BRICS economies converge to a sustainable equilibrium path in which environmental issues adjust with economic prosperity, population dynamics, and technological innovation. This convergence process supports the IPAT model's underlying hypothesis that population, affluence, and technology indicators will continuously converge to a steady-state equilibrium, ensuring long-run persistence. Fourth, the results provide empirical verification of the complex interlinkages among CO_2 emissions, GDP, PGP, LEO, and RNE in the BRICS economies and reiterate the IPAT model's applicability and validity as a theoretical prism for understanding and managing environmental persistence. By recognising the interlinkages among population, affluence, and technology, policymakers in

BRICS economies can conceptualise targeted, concerted measures that ensure sustainable prosperity and minimise ecological impacts, ultimately achieving long-run ecological and socioeconomic objectives.

5.1 Policy Implications and Recommendations

The empirical findings yield pragmatic, feasible policy outcomes across regions for policymakers in BRICS nations, including transitions in energy, population control, and sustainable economic development. Policymakers must invest in RNE infrastructure, such as solar, wind, and hydropower, and energy efficiency in industry, transportation, and agriculture. Some examples of such strategies include introducing tax credits for businesses that use energy-efficient processes, subsidizing RNE technologies, and advancing R&D for low-carbon technologies. Lastly, making affordable renewable energy accessible to rural and underserved communities is crucial for a successful transition to a widespread energy system. Policies should ensure family planning services to reduce long-term PGP-related CO_2 emissions, support the development of high-growth regions, and reduce fertility by promoting education in general and for women in particular. Access to microfinance for women and to rural development programs will also lower birth rates, as improved socioeconomic conditions reduce fertility. Finally, integrating population policies with urban affairs, health, and jobs will help manage demographic pressures sustainably.

Additionally, improving access to healthcare, clean water, sanitation, and social welfare programs is a prerequisite for lengthening life spans, which would likely reduce CO_2 emissions. Policymakers should also prioritize education and vocational training to develop a healthier, better-qualified workforce that drives green innovation and practices to improve economic and environmental sustainability. Green economic models decouple economic growth from environmental harm and would be strategically attuned to areas such as green business development, subsidizing corporation-to-corporation communication, encouraging eco-friendly practices, and investing in low-carbon infrastructure such as electric vehicle charging networks, sustainable transport systems, and waste-to-energy plants. Such would help induce the requisite economic growth while minimizing accompanying environmental degradation. Because this is a two-way, reciprocal relationship, such policies should align across most policy sectors. Interdisciplinary task forces or committees on energy, economics, the environment, and social welfare should be established to collaborate on coherent policy design. BRICS countries should also promote coordinated regional cooperation through joint research, technical transfers, and regional frameworks to integrate environmental and sustainable development policies.

These calls lead to the realization of the potential of sustainable policies by ensuring public awareness and stakeholder participation. Such educational campaigns help enlighten individuals and communities about the importance of achieving ecological sustainability and what they can do to achieve it. Further, inscribing stakeholder involvement through public consultations, public-private partnerships, or other community initiatives would ensure that policy directions are set close to local needs, thus enhancing the likelihood of broader acceptance. By following these steps, the BRICS states would better address the intertwined issues of emissions, GDP, population, life expectancy, and RNE.

5.2 Limitations and Future Research Suggestions

Nevertheless, the research brings out certain limitations despite its relevance. The analysis is conducted on BRICS countries alone, thereby limiting the applicability of the findings to other nations outside the BRICS group. Aggregate variables are used in the analysis, meaning that any variation in underlying factors, such as institutions, technology, and behavior, cannot be captured in detail. Insufficient data prevented the inclusion of additional environment-related and governance measures. Future research could focus on a more disaggregated analysis at the regional or even industry level to better understand the dynamics

underpinning the exploration. Also, a more comprehensive perspective on what influences environmental sustainability and economic development could be achieved by including variables such as technological change and external shocks.

Acknowledgement: None.

Funding Statement: The authors received no specific funding for this study.

Author Contributions: Seyma Caliskan Cavdar: original writing; data curation; editing; funding and proofreading while Festus Victor Bekun: conceptualization; methodology; Interpretation and interpretation and supervision. All authors reviewed and approved the final version of the manuscript.

Availability of Data and Materials: Data will be made available upon request.

Ethics Approval: Not applicable.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Moro KD, Xi J, Fumey MP, Awuye SK, Sackitey GM. Industrialization, energy demand and environmental pollution nexus in MINT economies. Does cleaner energy transition and environmental technology play a mitigating role? J Environ Manag. 2025;376(16):124451. doi:10.1016/j.jenvman.2025.124451.
2. Agarwal M, Kumar S. BRICS countries' increasing role in the world economy, including institutional innovation. Brics-Econ. 2023;4(2):173–91. doi:10.3897/brics-econ.4.e99451.
3. Chauvin JP, Glaeser E, Ma Y, Tobio K. What is different about urbanization in rich and poor countries? Cities in Brazil, China, India and the United States. J Urban Econ. 2017;98(15):17–49. doi:10.1016/j.jue.2016.05.003.
4. Alam MM, Murad MW, Noman AHM, Ozturk I. Relationships among carbon emissions, economic growth, energy consumption and population growth: testing Environmental Kuznets Curve hypothesis for Brazil, China, India and Indonesia. Ecol Indic. 2016;70(3):466–79. doi:10.1016/j.ecolind.2016.06.043.
5. Bhutto NA, Chang BH, Adeel S, Seelro AD, Qureshi MU. Global warming, economic development and their impact on the life expectancy: an empirical evidence from Pakistan. Stud Appl Econ. 2022;41(1):7875. doi:10.25115/sae.v41i1.7875.
6. Wiredu J, Yang Q, Sampene AK, Gyamfi BA, Asongu SA. The effect of green supply chain management practices on corporate environmental performance: does supply chain competitive advantage matter? Bus Strategy Environ. 2024;33(3):2578–99. doi:10.1002/bse.3606.
7. Muhammed G, Tekbiyik-Ersoy N. Development of renewable energy in China, USA, and Brazil: a comparative study on renewable energy policies. Sustainability. 2020;12(21):9136. doi:10.3390/su12219136.
8. Pathak L, Shah K. Renewable energy resources, policies and gaps in BRICS countries and the global impact. Front Energy. 2019;13(3):506–21. doi:10.1007/s11708-018-0601-z.
9. Azam M, Adeleye BN. Impact of carbon emissions sources on life expectancy in Asia and the Pacific region. Nat Resour Forum. 2024;48(1):35–57. doi:10.1111/1477-8947.12303.
10. Karma E. Socioeconomic determinants of life expectancy: southeastern European countries. Eur J Sustain Dev. 2023;12(1):25. doi:10.14207/ejsd.2023.v12n1p25.
11. Ehrlich PR, Holdren JP. Impact of population growth. Science. 1971;171(3977):1212–17. doi:10.1126/science.171.3977.1212.
12. Kissinger M, Karplus Y. IPAT and the analysis of local human–environment impact processes: the case of indigenous Bedouin towns in Israel. Environ Dev Sustain. 2015;17(1):101–21. doi:10.1007/s10668-014-9540-y.
13. Pickson RB, Gui P, Jian L, Boateng E. Do population-related factors matter for carbon emissions? Lessons from different income groups of countries. Urban Clim. 2024;55(3):101934. doi:10.1016/j.uclim.2024.101934.

14. Hasan MB, Wieloch J, Ali MS, Zikovic S, Uddin GS. A new answer to the old question of the environmental Kuznets Curve (EKC). Does it work for BRICS countries? Resour Policy. 2023;87(48):104332. doi:10.1016/j.resourpol.2023.104332.
15. Azevedo VG, Sartori S, Campos LMS. CO_2 emissions: a quantitative analysis among the BRICS nations. Renew Sustain Energy Rev. 2018;81(10):107–15. doi:10.1016/j.rser.2017.07.027.
16. Silvia V, Sartiyah, Fitra MR. Demand for Indonesian patchouli oil exports: the panel autoregressive distributed lag (ardl) approach. Rev De Gestão Soc E Ambiental. 2023;17(2):e03090. doi:10.24857/rgsa.v17n2-021.
17. Zhang H, Jin R, Ali Chandio A, Twumasi MA. A step toward the modern and sustainable agriculture: evaluating the impact of information and communication technology on cereal production in China. Sustain Dev. 2025;33(2):1989–2003. doi:10.1002/sd.3223.
18. Igwilo JI, Sibindi AB. ICT adoption and stock market development in Africa: an application of the panel ARDL bounds testing procedure. J Risk Financ Manag. 2021;14(12):601. doi:10.3390/jrfm14120601.
19. Awosusi AA, Adebayo TS, Kirikkaleli D, Altuntaş M. Role of technological innovation and globalization in BRICS economies: policy towards environmental sustainability. Int J Sustain Dev World Ecol. 2022;29(7):593–610. doi:10.1080/13504509.2022.2059032.
20. Mahalik MK, Le TH, Le HC, Mallick H. How do sources of carbon dioxide emissions affect life expectancy? Insights from 68 developing and emerging economies. World Dev Sustain. 2022;1(6):100003. doi:10.1016/j.wds.2022.100003.
21. Jalan D, Tuli A, Chaudhary V, Sharma N, Rakhra M. Machine learning models for life expectancy. In: Proceedings of the 2023 International Conference on Artificial Intelligence and Applications (ICAIA) Alliance Technology Conference (ATCON-1); 2023 Apr 21–22; Bangalore, India. p. 1–6. doi:10.1109/icaia57370.2023.10169737.
22. Bali V, Aggarwal D, Singh S, Shukla A. Life expectancy: prediction & analysis using ML. In: Proceedings of the 2021 9th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions) (ICRITO); 2021 Sep 3–4; Noida, India. New York, NY, USA: IEEE; 2021. p. 1–8. doi:10.1109/icrito51393.2021.9596123.
23. Bulut Ş, Ağıralioğlu S. Comparison of factors affecting the level of living in countries with different income groups. Uluslararası Ekon İşletme Ve Polit Derg. 2022;6(2):278–97. doi:10.29216/ueip.1135465.
24. Younus S, Khursheed A, Afzal N. Impact of economic progress, energy consumption and carbon dioxide emissions on life expectancy: evidence from Asia and Africa. J Soc Sci Rev. 2022;2(3):225–35. doi:10.54183/jssr.v2i3.115.
25. Li C, Sampene AK, Agyeman FO, Brenya R, Wiredu J. The role of green finance and energy innovation in neutralizing environmental pollution: empirical evidence from the MINT economies. J Environ Manage. 2022;317(38):115500. doi:10.1016/j.jenvman.2022.115500.
26. Talwariya A, Singh P, Jobanputra JH, Kolhe ML. Machine learning based renewable energy generation and energy consumption forecasting. Energy Sources Part A Recovery Util Environ Eff. 2023;45(2):3266–78. doi:10.1080/15567036.2023.2194257.
27. Simionescu M, Rădulescu M, Cifuentes-Faura J. Renewable energy consumption-growth nexus in European countries: a sectoral approach. Eval Rev. 2023;47(2):287–319. doi:10.1177/0193841x221125982.
28. Wang Q, Yang X, Li R, Yang T. Revisiting the impact of renewable energy on carbon emission in 130 countries—the mediating effect of resource rental rents and human capital. Energy Environ. 2024;35(8):4083–113. doi:10.1177/0958305x231177726.
29. Mirziyoyeva Z, Salahodjaev R. Renewable energy, GDP and CO_2 emissions in high-globalized countries. Front Energy Res. 2023;11:1123269. doi:10.3389/fenrg.2023.1123269.
30. Elbadri M, Bsikre S, Alamari O, Balcilar M. Nexus between renewable energy consumption, economic growth, and CO_2 emissions in Algeria: new evidence from the Fourier-Bootstrap ARDL approach. Nat Resour Forum. 2023;47(3):393–412. doi:10.1111/1477-8947.12292.
31. Guo X, Huang K, Li L, Wang X. Renewable energy for balancing carbon emissions and reducing carbon transfer under global value chains: a way forward. Sustainability. 2023;15(1):234. doi:10.3390/su15010234.
32. Mukhtarov S, Aliyev F, Aliyev J, Ajayi R. Renewable energy consumption and carbon emissions: evidence from an oil-rich economy. Sustainability. 2023;15(1):134. doi:10.3390/su15010134.

33. Ulucak R, Danish, Zhang Y, Chen R, Qiu Y. Income inequality, economic complexity, and renewable energy impacts in controlling consumption-based carbon emissions. Eval Rev. 2024;48(1):119–42. doi:10.1177/0193841x231173766.
34. Perone G. The relationship between renewable energy production and CO_2 emissions in 27 OECD countries: a panel cointegration and Granger non-causality approach. J Clean Prod. 2024;434(4):139655. doi:10.1016/j.jclepro.2023.139655.
35. Ali A, Radulescu M, Balsalobre-Lorente D. A dynamic relationship between renewable energy consumption, nonrenewable energy consumption, economic growth, and carbon dioxide emissions: evidence from Asian emerging economies. Energy Environ. 2023;34(8):3529–52. doi:10.1177/0958305x231151684.
36. Raihan A, Chandra Voumik L. Carbon emission reduction potential of renewable energy, remittance, and technological innovation: empirical evidence from China. J Technol Innov Energy. 2022;1(4):25–36. doi:10.56556/jtie.v1i4.398.
37. Dissanayake H, Perera N, Abeykoon S, Samson D, Jayathilaka R, Jayasinghe M, et al. Nexus between carbon emissions, energy consumption, and economic growth: evidence from global economies. PLoS One. 2023;18(6):e0287579. doi:10.1371/journal.pone.0287579.
38. Jia J, Rong Y, Chen C, Xie D, Yang Y. Contribution of renewable energy consumption to CO_2 emissions mitigation: a comparative analysis from the income levels' perspective in the Belt and Road initiative (BRI) region. Int J Clim Change Strateg Manag. 2021;13(3):266–85. doi:10.1108/ijccsm-06-2020-0053.
39. O'Sullivan J. Climate change and world population. In: The impacts of climate change. Amsterdam, The Netherlands: Elsevier; 2021. p. 313–50. doi:10.1016/b978-0-12-822373-4.00008-2.
40. Lawal IM. Impact of population growth on Carbon Dioxide (CO_2) emission: empirical evidence from Nigeria. J Perspektif Pembiayaan Dan Pembangunan Daerah. 2019;6(6):701–8. doi:10.22437/ppd.v6i6.6730.
41. Sikdar C, Mukhopadhyay K. Impact of population on carbon emission: lessons from India. Asia Pac Dev J. 2017;23(1):105–32. doi:10.18356/b4c7cba0-en.
42. York R, Rosa EA, Dietz T. STIRPAT, IPAT and ImPACT: analytic tools for unpacking the driving forces of environmental impacts. Ecol Econ. 2003;46(3):351–65. doi:10.1016/S0921-8009(03)00188-5.
43. Casey GP, Galor O. Population growth and carbon emissions? SSRN J. 2016:22885. doi:10.3386/w22885.
44. Ahmad TI, Bhatti MA, Urooj K, Javed H. Urban population growth, per capita energy use, and CO_2 emissions: evidence from the world's fifth-most populous country. IRASD J Ener Envio. 2022;3(2):97–110. doi:10.52131/jee.2022.0302.0029.
45. O'Neill BC, Dalton M, Fuchs R, Jiang L, Pachauri S, Zigova K. Global demographic trends and future carbon emissions. Proc Natl Acad Sci USA. 2010;107(41):17521–6. doi:10.1073/pnas.1004581107.
46. Zarco-Periñán PJ, Zarco-Soto IM, Zarco-Soto FJ. Influence of population density on CO_2 emissions, eliminating the influence of climate. Atmos. 2021;12(9):1193. doi:10.3390/atmos12091193.
47. Liu Y, Chen J. Mapping global population changes. In: Atlas of global change risk of population and economic systems. Singapore: Springer Nature; 2022. p. 87–94. doi:10.1007/978-981-16-6691-9_5.
48. Gaffin SR. World population projections for greenhouse gas emissions scenarios. Mitig Adapt Strateg Glob Change. 1998;3(2):133–70. doi:10.1023/a:1009637812445.
49. Fang P. Short-term carbon emission prediction method of green building based on IPAT model. Int J Glob Energy Issues. 2023;45(1):1. doi:10.1504/ijgei.2023.127664.
50. Shen Y, Hu S, Ma H, Huang P, Ma J. Prediction of the path level of carbon emission reduction based on the IPAT model from the computer vision. In: Application of intelligent systems in multi-modal information analytics. Cham, Switzerland: Springer International Publishing; 2022. p. 416–23. doi:10.1007/978-3-031-05484-6_52.
51. Kayani UN, Sadiq M, Rabbani MR, Aysan AF. Examining the relationship between economic growth, financial development, and carbon emissions: a review of the literature and scientometric analysis. Int J Energy Econ Policy. 2023;13(2):489–99. doi:10.32479/ijeep.14278.
52. Zhang J, Zhang Y. Examining the economic and environmental effects of emissions policies in China: a Bayesian DSGE model. J Clean Prod. 2020;266(2–4):122026. doi:10.1016/j.jclepro.2020.122026.

53. Huang Z. Analyze the relationship between CO2 emissions and GDP from the global perspective. In: Proceedings of the Advances in Economics, Business and Management Research; 2021 Aug 27–29; Guangzhou, China. Paris: FranceAtlantis Press; 2021. p. 442–51. doi:10.2991/aebmr.k.210917.068.
54. Khalfaoui R, Tiwari AK, Khalid U, Shahbaz M. Nexus between carbon dioxide emissions and economic growth in G7 countries: fresh insights via wavelet coherence analysis. J Environ Plan Manag. 2023;66(1):31–66. doi:10.1080/09640568.2021.1978062.
55. Huh T. Comparative and relational trajectory of economic growth and greenhouse gas emission: coupled or decoupled? Energies. 2020;13(10):2550. doi:10.3390/en13102550.
56. Destek MA, Shahbaz M, Okumus I, Hammoudeh S, Sinha A. The relationship between economic growth and carbon emissions in G-7 countries: evidence from time-varying parameters with a long history. Environ Sci Pollut Res Int. 2020;27(23):29100–17. doi:10.1007/s11356-020-09189-y.
57. Bilgili F, Koçak E, Bulut Ü. The dynamic impact of renewable energy consumption on CO_2 emissions: a revisited environmental Kuznets Curve approach. Renew Sustain Energy Rev. 2016;54(9):838–45. doi:10.1016/j.rser.2015.10.080.
58. WDI. World Development Indicator Database [Internet]. Available from: https://databank.worldbank.org/source/world-development-indicators.
59. Dietz T, Rosa EA. Rethinking the environmental impacts of population, affluence and technology. Hum Ecol Rev. 1994;1(2):277–300. doi:10.4324/9780203011751.ch6.
60. Zhao K, Cui X, Zhou Z, Huang P, Li D. Exploring the dependence and influencing factors of carbon emissions from the perspective of population development. Int J Environ Res Public Health. 2021;18(21):11024. doi:10.3390/ijerph182111024.
61. Pesaran MH. Testing weak cross-sectional dependence in large panels. Econom Rev. 2015;34(6–10):1089–117. doi:10.1080/07474938.2014.956623.
62. Pedroni P. Critical values for cointegration tests in heterogeneous panels with multiple regressors. Oxford Bull Econ Stats. 1999;61(s1):653–70. doi:10.1111/1468-0084.61.s1.14.
63. Dumitrescu EI, Hurlin C. Testing for Granger non-causality in heterogeneous panels. Econ Model. 2012;29(4):1450–60. doi:10.1016/j.econmod.2012.02.014.
64. Breusch TS, Pagan AR. The Lagrange multiplier test and its applications to model specification in econometrics. Rev Econ Stud. 1980;47(1):239. doi:10.2307/2297111.