Environmental Impact Assessment Review 115 (2025) 107993

Contents lists available at ScienceDirect

Environmental Impact Assessment Review

journal homepage: www.elsevier.com/locate/eiar

Green transition initiatives to reduce environmental degradation: Adaptation, mitigation and synergistic effects

Binlin Li [a], Mohammad Mafizur Rahman [b], Nils Haneklaus [c,d,*], Shuqin Li [e], Yufei Zhou [e]

[a] College of Economics and Management, Yunnan Agricultural University, Kunming, China
[b] School of Business, University of Southern Queensland, Australia
[c] Td-Lab Sustainable Mineral Resources, University for Continuing Education Krems, Dr.-Karl-Dorrek-Straße 30, 3500 Krems an der Donau, Austria
[d] Unit for Energy and Technology Systems - Nuclear Engineering, North-West University, 11 Hoffman Street, Potchefstroom 2520, South Africa
[e] College of Economics, Ocean University of China, Qingdao 266100, PR China

A R T I C L E I N F O

Keywords:
Ecological footprint (EF)
Load capacity factor (LF)
STIRPAT
Green transition
FMOLS
MMQR

A B S T R A C T

Green transitions are crucial strategies for mitigating environmental degradation and are aligned with the Sustainable Development Goals (SDGs) of the United Nations such as SDG 7, SDG 11 and SDG 13. This study used an expanded STIRPAT framework to investigate the adaptation, mitigation, and synergistic effects of green transition variables, namely, Renewable Energy Transition (RES), Green Finance (GFC) and Green Technology (GT). Ecological Footprint (EF) and Load Capacity Factor (LF) indicators were integrated to overcome the limitations of CO_2-centric indicators towards environmental degradation. Empirical analysis employs structured methods, including heteroskedasticity-robust panel unit root tests, long-run estimation (FMOLS), asymmetric effects (MMQR), and robustness checks (panel EGLS and D-H causality tests). The FMOLS results indicate that RES, GFC and GT create a synergistic governance framework that amplifies their individual impacts. GFC supports the R&D and deployment of GT, while GT optimizes the performance of RES projects. RES accelerates the adoption of renewables, enhancing energy efficiency and further reducing environmental degradation. MMQR results show that RES consistently reduces EF and increases LF across all quantiles, highlighting its key role in mitigating degradation. GFC exhibits varied effects across quantiles, while GT has significant positive effects on LF in lower to middle quantiles and reduces EF in higher quantiles. However, its impact on both LF and EF is less pronounced compared to that of RES and GFC. The insights gained here from the G-6 countries serve as a valuable guide or emerging economies, such as those of the BRICS, in developing adaptation and mitigation strategies to navigate the trade-offs between socio-economic developments and ecological thresholds.

1. Introduction

The green transition involves shifting to a sustainable, resource-efficient economy to address climate change and environmental degradation. Transition strategies, such as the European Green Deal, aim for climate neutrality to ensure a just and inclusive transformation (EU, 2020). However, deep-rooted structural interdependencies within the economy, resource depletion, and population dynamics, pose substantial barriers to effective green transition. These interdependencies, embedded in economic systems and patterns of resource use, potentially hinder rapid changes. This necessitates integrated adaptation and mitigation strategies for combating environmental degradation, improving quality of life and facilitating sound transition (Sakariyahu et al., 2024). Both strategies are interdependent, with inherent synergies and trade-offs, and must be implemented within the broader framework of green growth (Qin et al., 2023).

While the global community is increasingly aware of the challenges posed by environmental degradation, economic expansion often leads to ecological deficits and reduces the Earth's capacity to sustain human life (Anu et al., 2023; Gu et al., 2024). As shown in Fig. 1a, the Ecological Footprint (EF) exceeds the Earth's biocapacity in most of the G7 countries (excluding Canada) and also the BRICS countries, resulting in significant ecological deficits. This growing urgency calls for robust environmental and natural resource management frameworks, particularly for countries whose economies rely heavily on non-renewable resources. The management practices in these countries significantly

* Corresponding author at: Td-Lab Sustainable Mineral Resources, University for Continuing Education Krems, Dr.-Karl-Dorrek-Straße 30, 3500 Krems an der Donau, Austria

E-mail address: nils.haneklaus@donau-uni.ac.at (N. Haneklaus).

https://doi.org/10.1016/j.eiar.2025.107993
Received 6 January 2025; Received in revised form 14 May 2025; Accepted 15 May 2025
Available online 21 May 2025

impact both global populations and environmental sustainability (Sakariyahu et al., 2024).

Furthermore, the EF has emerged as a comprehensive ecological indicator that goes beyond CO_2, drawing increasing attention in recent research (Dam and Sarkodie, 2023; Kish and Miller, 2025; Sarwar et al., 2024). Recent studies further highlight the significance of the Load Capacity Factor (LF) as a key ecological indicator, emphasizing its utility in capturing the complexities of environmental degradation (Han and Sun, 2024; Musah et al., 2024; Uche et al., 2024; Sun et al., 2024a). The LF offers a more comprehensive perspective by incorporating both demand and supply aspects (Adebayo and Samour, 2024), enabling a clearer evaluation of environmental security by distinguishing between EF and biocapacity (Mehmood et al., 2023). However, it does not adequately address the situation in countries facing ecological deficits (Dam and Sarkodie, 2023). As a result, this work is motivated by integrating both EF and LF. Researchers and policymakers can accurately assess environmental sustainability of national practices and develop strategies to ensure long-term environmental management.

As shown in Fig. 1b, Canada is classified as a biocapacity reserve country, with a biocapacity of 8 gha per person in 2000 and 7.5 gha per person in 2022. In contrast, the other G7 countries are categorized as biocapacity deficit countries. Thus, this study focuses on countries with comparably high levels of industrialization, energy consumption, and ecological deficits, excluding Canada. Moreover, Fig. 2 compares the BRICS countries with the G-6 countries across indicators such as economic development, natural resource depletion, population density, and biocapacity deficit (defined as biocapacity minus EF), revealing significant disparity in both economic and environmental metrics. While the

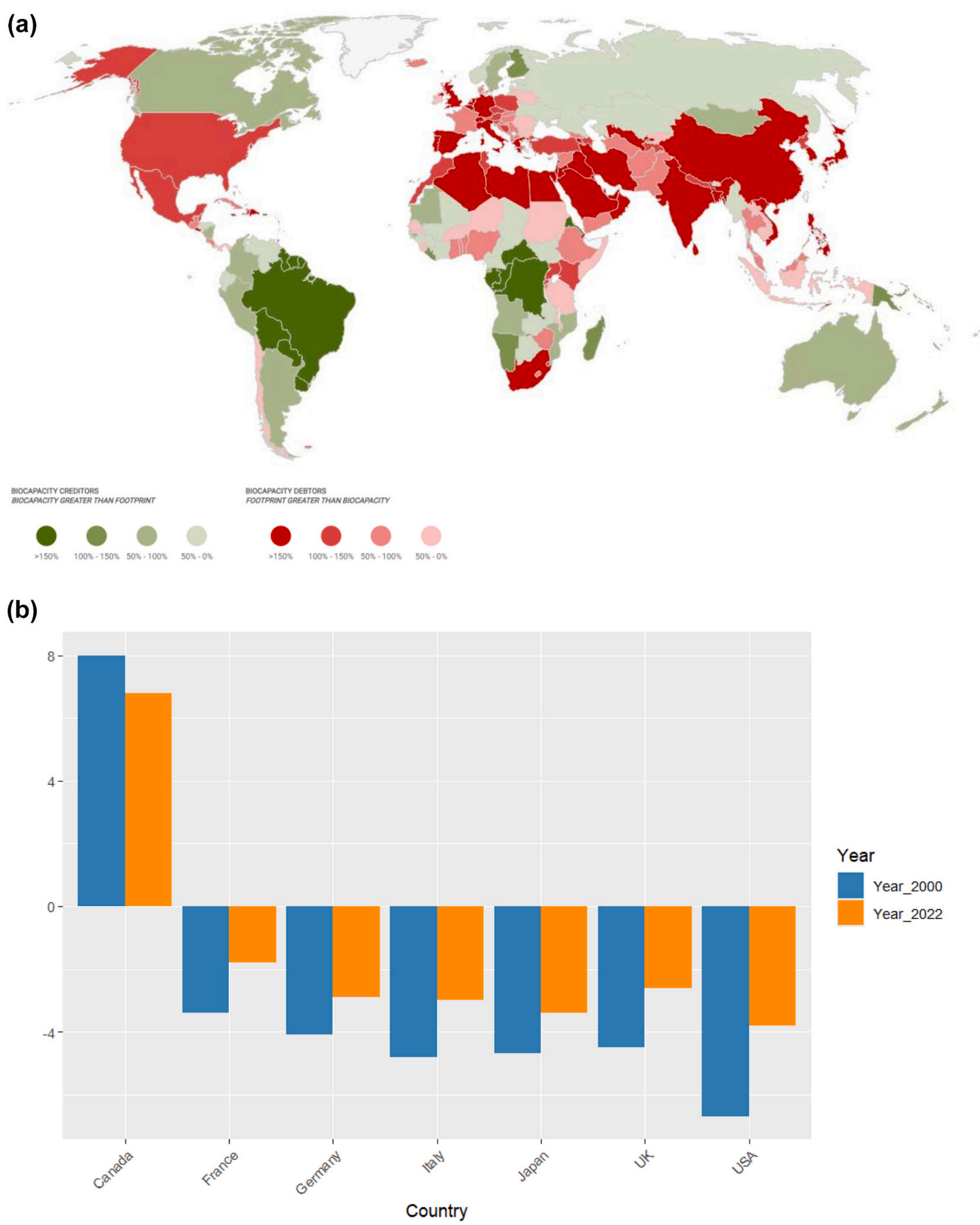

Fig. 1. a. Global distribution of ecological indicators showing countries with biocapacity deficit (−) and reserves (+) (Datasource: Global Footprint Network). b. The biocapacity deficit values for G-7 countries in 2000 and 2022. Canada's exclusion is justified due to its distinctive biocapacity reserve (6.8 gha per person in 2022), resulting in the analysis focusing on the G-6 countries (Datasource: Global Footprint Network).

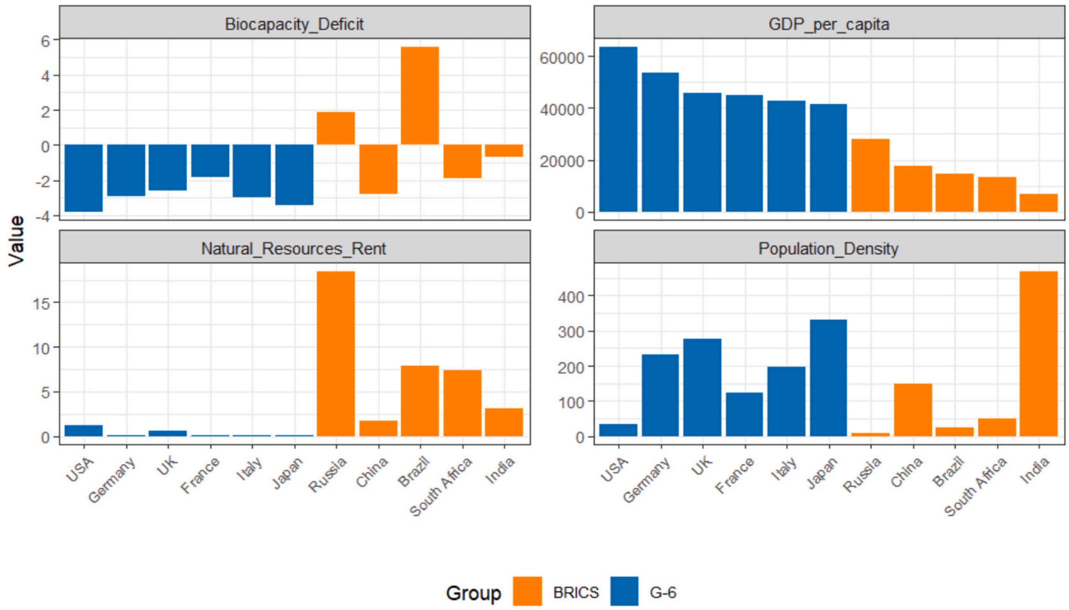

Fig. 2. BRICS vs. G-6 countries across key indicators (Data source: Global Footprint Network, World Bank, OECD).

BRICS countries exhibit lower GDP per capita and higher population density than the G-6 countries, BRICS countries rely more heavily on natural resources use, increasing the vulnerability to market fluctuations. Additionally, Fig. 3 illustrates that the G-6 countries have achieved notable environmental improvements, as evidenced by the trend of both EF and LF. These analysis emphasizes the significance of the green transition strategies deployed by the G-6 countries, providing potential insights for developing countries or emerging economies such as the BRICS countries.

The Stochastic Impacts by Regression on Population, Affluence, and

Fig. 3. Time-varying evolution of EF and LF in past 3 decades for G-6 countries (Data source: Global Footprint Network).

Technology (STIRPAT) model provides a systematic framework for evaluating the influence of demographic, economic, and technological factors on the environment, providing valuable scientific evidence and policy recommendations (Quan et al., 2024). The results of the extended STIRPAT models can demonstrate environmental health by incorporating the supply and demand aspects of the nature (Sun et al., 2024b). However, empirical findings may vary due to differences in model specifications, control variables, and proxies for key concepts (Schneider, 2022). This study seeks to extend the STIRPAT framework to address these discrepancies, thereby clarifying the complex interactions between human activities and environmental impacts.

This work makes significant contributions to address gaps in the following ways: (i) By employing an expanded STRIPAT model, we provide novel insights into the dynamic relationship between the green transition and environmental degradation. The analysis integrates key socio-economic variables such as GDP, natural resource depletion, and population density. Focusing on G-6 countries with comparable industrialization, energy consumption, and biocapacity deficits allows for a comprehensive understanding of how green transitions impact environmental degradation. (ii) This study fills existing research gaps by examining the adaptation, mitigation, and synergistic effects of renewable energy transition (RES), green finance (GFC), and green technology (GT) in reducing environmental degradation. The findings offer valuable lessons for sustainable development strategies and environmental impact mitigation, particularly for developing countries (e.g., BRICS). (iii) This study incorporates both EF and LF as indicators of environmental degradation, revealing dynamic performance of ecological sustainability in G-6 countries. The insights inform targeted green transition strategies and policy interventions aligned with the Sustainable Development Goals (SDGs) of the United Nations. (iv) The study uses advanced econometric techniques, including heteroskedasticity-robust panel unit root tests, Method of Moments Quantile Regression (MMQR), Fully Modified Ordinary Least Squares (FMOLS), and panel Estimated Generalized Least Squares (panel EGLS), to systematically display how green transitions drive dynamic trends in environmental degradation.

The remainder of the paper is structured as follows: Section 2 provides a comprehensive literature review. Section 3 outlines the theoretical model in this study. Section 4 details the econometric methodology and data description. Section 5 presents the empirical results and discussion. Section 6 conducts a robustness analysis. Finally, Section 7 shows the conclusions, policy implications, and limitations of the study.

2. Literature review

Ambitious climate policies, alongside economic expansion, technological progress and the promotion of less resource-intensive lifestyles, are essential elements for advancing the UN SDGs (Soergel et al., 2021). This global imperative to combat climate change and environmental degradation has driven the growing prominence of green transition strategies. This brief literature review extracts insights from previous analyses in environmental economics, which have focused on environmental degradation indicators and the dynamics among economies, resources and populations. Furthermore, it presents the findings and highlights the critical role of RES, GFC and GT in facilitating the transition, as identified in prior studies.

2.1. Conceptualizing environmental degradation: Multiple key indicators

Environmental degradation is a complex process involving negative impacts on the natural environment, such as deforestation, pollution, ecosystem disruption, biodiversity loss, and resource depletion. These challenges are primarily driven by anthropogenic activities such as urban waste, inadequate recycling, and unsustainable economic growth (Koengkan et al., 2023). The diverse indicators of environmental degradation, alongside the inclusion of other key variables and economic expansion as factors in environmental degradation, have sparked debate among policymakers (Villanthenkodath et al., 2024a). As the effects of environmental degradation and climate change intensify, analyzing the interactions of key variables, such as clean energy use, eco-technological innovation, and other critical factors, becomes increasingly critical (Ul-Durar et al., 2024).

CO_2 emissions have been frequently considered a primary indicator of ecological degradation. For example, Li et al. (2024) explored how financial technologies, digitalization, natural resources, and human resources affect degradation indicators (CO_2 emissions) across G20 countries from 2000 to 2021. However, Mehmood et al. (2023) claimed that relying on CO_2 emissions alone does not fully account for the broader impacts of human activities on various environmental dimensions, such as water, land, and biodiversity. Recent studies have highlighted the need for more comprehensive indicators, such as the ecological footprint and load capacity factor, to capture the full scope of environmental degradation. Villanthenkodath and Pal (2024) incorporated EF, CO_2, and LF to create a more comprehensive econometric framework for assessing environmental degradation in India. CO_2 emissions are widely regarded as a key indicator of environmental degradation. For instance, Li et al. (2024) investigated how financial technologies, digitalization, natural resources, and human capital influenced CO_2 in G20 countries between 2000 and 2021. Mehmood et al. (2023) argued that relying on CO_2 as the main indicator fails to account for broader environmental degradation impacts (e.g., water, land, and biodiversity). Recent studies have emphasized the importance of using EF and LF to better capture the border metrics of environmental degradation. For example, Hakkak et al. (2023) analyzed the effects of nuclear and renewable energy consumption on environmental degradation in Russia, using EF and LF as indicators of environmental degradation. Dam et al. (2024) utilized CO_2, EF and inverted LF to represent degradation indicators.

This shift towards indicators like EF and LF improves the assessment of environmental impacts, including air and water pollution, soil erosion, desertification, and ecological disruptions, thereby supporting the effective adaptation and mitigation strategies.

2.2. Analyzing drivers of degradation: STIRPAT frameworks

The STIRPAT model has been regarded as a robust analytical framework for displaying the complex dynamics between population, affluence, technological advancements, and environmental impacts (Schneider, 2022). The framework provides an indispensable tool in environmental economics by estimating elasticities (Schneider, 2022). For instance, Touati and Ben-Salha (2024) used the STIRPAT model to investigate the dynamic interaction between resource abundance, energy demand, economic openness, population growth, urbanization and environmental degradation.

Debates persist regarding the magnitude and significance of population, affluence and technology elasticities in the STIRPAT models. For example, Xing et al. (2023) highlighted the role of technological innovation in sustainable development in Asian economies using advanced econometric techniques from 1990 to 2017. Similarly, Touati and Ben-Salha (2024) analyzed the impacts of digitalization, industrialization, and financial development on environmental sustainability in Gulf Cooperation Council (GCC) countries between 2000 and 2021. Shazhad and Aruga (2024) identified an Environmental Kuznets Curve (EKC) in Asia through spatial econometric analysis, showing a turning point in environmental degradation. Wang and Taghvaee (2023) explored how economic complexity and technology can influence pollution and growth in both developed and developing regions from 1971 to 2017.

STIRPAT-related studies reveal disparities in the estimated elasticities, primarily due to differences in model specifications, variables, time periods, and econometric approaches. Key econometric challenges include model specification heterogeneity, data non-stationarity, uncontrolled cross-sectional dependence, heterogeneous slopes, and non-standardized coefficients (Schneider, 2022). Schneider (2022) emphasizes the need for standardized methodologies, robust unit root tests, and using spatial and temporal heterogeneities to address the limitations. As a result, expanding STIRPAT frameworks and strengthening theoretical hypotheses using country-specific panel dataset is crucial for revealing the dynamic elasticities of key drivers, and ensuring reliable policy recommendations.

2.3. Transitioning towards environmental sustainability: The roles of renewables, green technology, green finance

Recent studies highlight the importance of collective action in transitioning towards environmental sustainability, particularly emphasizing equitable treatment, climate justice, and global cooperation in mitigating global warming and addressing energy crises (Doumon, 2024).

Empirical studies highlight the pivotal role of renewable energy and green technologies for ecological sustainability through their synergistic effects. Environmental policy significantly decreases EF by promoting renewables and innovation (Sohag et al., 2024). Javed et al. (2024) investigated the interactions among green technology, environmental policy, and renewables, economic growth, trade openness, and urbanization on the EF of the G7 economies. Sharif et al. (2024) examined the combined impact of green technology, renewable energy, and globalization on environmental sustainability in countries most affected by ecological challenges. Ul-Durar et al. (2024) reinforced the importance of renewable energy and green technology in mitigating ecological risks and supporting indispensable roles in global environmental strategies. Pal et al. (2025) found that renewable energy production can lead to increased CO_2 emissions in emerging economies but significantly reduces CO_2 emissions in OECD countries. Notably, technology-moderated renewable energy production effectively lowers CO_2 emissions across both groups. The mechanism by which renewable energy reduces the reliance on fossil fuels helps to mitigate environmental degradation, thereby emphasizing the need for ongoing technological innovation in renewable energy development to further reduce the EF (Villanthenkodath and Pal, 2024). Ma et al. (2024) investigated the dynamics between natural resource rents, ecological policies, technology, economic growth, and the EF in the top and least green growth countries, revealing a negative relationship between EF and renewables, technological change.

Furthermore, growing global concerns regarding environmental degradation have heightened interests in sustainable financial support, generating increasing advocacy for eco-friendly financing initiatives as viable solutions for achieving ecological sustainability (Sun and Rasool, 2024). Wang et al. (2024) investigated the influence of fintech and green finance on the environment of mineral-rich developing nations, employing three distinct regression models to assess the effects on CO_2-, NO_2-emissions and the EF. The findings highlight the necessity for enhanced fintech development, prioritization of green finance, and commitment to balanced economic growth as essential pathways towards sustainable and eco-conscious development in resource-dependent economies. Delving into the nexus of green finance and ecological sustainability, Sun and Rasool (2024) analyzed the asymmetric relationship between green finance and EF in ten leading European countries with significant green finance investments, confirming a negative association. In the context of China, Zhang and Chen (2023) examined the role of green finance on EF from the first quarter of 1998 to the fourth quarter of 2020, revealing that green finance initiatives substantially contribute to reduce EF over time. Villanthenkodath et al. (2024b) emphasized the critical role of monetary policy in integrating the renewables into policy frameworks to achieve sustainability. This work also highlights the importance of implementing other policy interventions that prioritize ecological conservation alongside economic development, ensuring a balanced and comprehensive approach to addressing both environmental and economic challenges.

In general, green transitions pose distinct challenges for developed and developing economies. Developed countries typically possess greater access to financial resources, technological innovation, and institutional frameworks, enabling more rapid decarbonization. In contrast, developing economies require financing and technology transfers to bridge biocapacity deficit. Achieving sustainable futures necessitates collective action, climate justice, and context-specific policies.

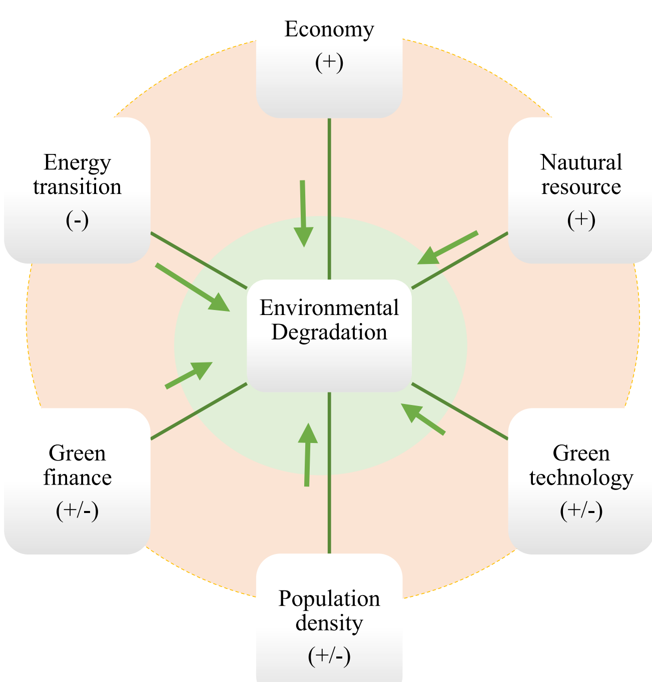

Fig. 4. A flow chart illustrating the theoretical hypothesis based on the STIRPAT model.

2.4. Research gaps

This study was designed to address the following underexplored areas in the existing literature. (i) To the best of our knowledge, prior studies have not extended the STIRPAT model to include environmental degradation indicators (EF and LF) alongside drivers such as socio-economic variables (GDP, NRS, POP) and green transition indicators (RES, GF, GT) in panel data analyses. (ii) Previous studies have not adequately examined the long-run cointegration relationships and quantile-specific dynamics between green transition variables and environmental degradation within the STIRPAT framework. This limitation restricts using advanced econometric techniques (e.g., FMOLS and MMQR) to reveal the adaptive, mitigating, and synergistic effects of green transition initiatives in promoting environmental sustainability. (iii) While existing studies often focuses on the OECD or G7, there is a significant gap in analyzing green transition strategies of G-6 countries. These economies share comparable socio-economic and environmental contexts, creating a homogeneous panel for transition pathways. (iv) Prior studies seldom provide implications for aligning green transition initiatives with SDGs targets. Moreover, there is limited discussion of practical, flexible, and scalable transition pathways, particularly in designing inclusive, replicable pathways to both developed and developing economies.

3. Theoretical model

Introduced by Dietz and Rosa (1997), the STIRPAT model breaks down the total environmental impact (I) into the impact of population (P), affluence or increased use of natural resources (A), and technology (T). The original STIRPAT model can be expressed as shown in Eq. (1):

$$I_{it} = aP_{it}^{b}A_{it}^{c}T_{it}^{d}e_{it} \tag{1}$$

To align with econometric practices and make the parameters easier to interpret, Eq. (1) is transformed into logarithmic form (Eq. (2)). In this form, the original exponents b, c, and d are redefined as elasticity parameters β, γ and φ.

$$\ln I_{it} = \alpha + \beta \ln P_{it} + \gamma \ln A_{it} + \varphi \ln T_{it} + \varepsilon_{it} \tag{2}$$

Here, i indexes the cross-sectional units (G-6 countries) and *t* denotes the time period.

Motivated by Dam et al. (2024), this study seeks to expand the traditional STIRPAT model by incorporating key variables, including GDP, NRS, POP and indicators related to green transitions, such as GF, RES and GF. By integrating these variables, the study aims to investigate the impact of various drivers on environmental degradation, with a specific focus on EF and LF. This analysis is conducted by eqs. (3) and (4), which show the consumption and supply dimensions of environmental degradation, respectively.

$$\ln EF_{it} = \alpha + \varphi_1 \ln GDP_{it} + \varphi_2 \ln NRS_{it} + \varphi_3 \ln POP_{it} + \varphi_4 \ln GT_{it} + \varphi_5 \ln RES_{it} + \varphi_6 \ln GF_{it} + \varepsilon_{it} \tag{3}$$

$$\ln LF_{it} = \alpha + \varphi_1 \ln GDP_{it} + \varphi_2 \ln NRS_{it} + \varphi_3 \ln POP_{it} + \varphi_4 \ln GT_{it} + \varphi_5 \ln RES_{it} + \varphi_6 \ln GF_{it} + \varepsilon_{it} \tag{4}$$

Where α represents the intercept term, $\varphi_1 \sim \varphi_6$are long-run coefficients, and ε_{it} denotes error terms.

As depicted in Fig. 4, the visual hypothesis helps clarify how different factors influence environmental degradation, providing a basis for further econometric analysis and policy implications.

4. Econometric strategies and data

Fig. 5 presents the econometric strategies utilized in this study, along with the rationale behind these methods. This structured framework ensures robustness, systematicity, and reliability in the analysis.

4.1. Heteroskedasticity-robust panel unit root tests

Panel datasets often exhibit cross-sectional heteroskedasticity, which may violate the homoskedasticity assumption underlying traditional unit root tests. In addition, the Cauchy estimator employs the sign of the first lag as an instrumental variable in autoregressions, avoiding nonstandard asymptotic in traditional unit root tests (e.g., ADF) (Matei and Christoph, 2010). Motivated by Herwartz et al. (2018), this study uses panel unit root tests (PURTs) that integrate the Cauchy estimator. PURTs maintain reliability while reducing potential biases associated with the heteroskedasticity. The procedure can be articulated as follows:

A first-order panel autoregression model can be formulated without or with μ term, as represented in eqs. (5) and (6), respectively.

$$\boldsymbol{y}_t = (1-\rho)\boldsymbol{\mu} + \rho \boldsymbol{y}_{t-1} + \varepsilon_t \tag{5}$$

$$\boldsymbol{y}_t = \mu + (1-\rho)\boldsymbol{\delta} t + \rho \boldsymbol{y}_{t-1} + \varepsilon_t \tag{6}$$

Where $\boldsymbol{y}_t = (y_{1t}, \ldots, y_{Nt})'$ and $\boldsymbol{y}_{t-1} = \left(y_{1,t-1}, \ldots, y_{N,t-1}\right)'$, which both are represented as a $N \times 1$ vectors, and error term ε_t is heterogeneously distributed with a mean of zero. In the context of panel data models, the null hypothesis H_0 suggests a driftless random walk, whereas H_1 indicates a stationary process.

The white-type test, denoted by Eq. (7) as t_{HS} is robust to heteroskedasticity. Additionally, by utilizing a White-type covariance analysis, a PURT can be robust to cross-sectional dependence.

$$t_{HS} = \frac{\sum_{t=1}^{T} \boldsymbol{y}_{t-1}' \Delta \boldsymbol{y}_t}{\sqrt{\sum_{t=1}^{T} \boldsymbol{y}_{t-1}' \widehat{\boldsymbol{e}}_t \widehat{\boldsymbol{e}}_t' \boldsymbol{y}_{t-1}}} \rightarrow dN(0,1) \tag{7}$$

The White-type Cauchy test, denoted by t_{DH} in Eq. (8), employs a heteroskedasticity-robust technique that uses the “Cauchy” estimator. This estimator incorporates the sign function sgn(·) for the lagged level series.

$$t_{DH} = \frac{\sum_{t=1}^{T} \mathrm{sgn}(\boldsymbol{y}_{t-1})' \Delta \boldsymbol{y}_t}{\sqrt{\sum_{t=1}^{T} \mathrm{sgn}(\boldsymbol{y}_{t-1})' \widehat{\boldsymbol{e}}_t \widehat{\boldsymbol{e}}_t' \mathrm{sgn}(\boldsymbol{y}_{t-1})}} \xrightarrow{d} N(0,1) \tag{8}$$

4.2. Cross-sectional dependence (CD) test and slope homogeneity test

Grossman and Krueger (1995) argue that ignoring cross-sectional dependence in panel data analysis can result in inconsistent parameter estimates, while Breitung (2005) emphasizes that assuming slope homogeneity in the presence of heterogeneity may lead to biased estimation.

The heterogeneous panel data model is represented by Eq. (9):

$$y_{it} = x_{it}'\beta_i + u_{it}, \text{for } i = 1, \ldots, n; t = 1, \ldots, T \tag{9}$$

where y_{it} denotes the dependent variable for cross-sectional unit i at time t. x_{it}' represents the exogenous regressors, and β_i are the slope parameters. The error term $u_{it}$is assumed to exhibit cross-sectional dependence but remains uncorrelated with the regressors x_{it}'. The fixed effects homogeneous model with the idiosyncratic error of v_{it} is shown in Eq. (10):

$$y_{it} = \alpha + x_{it}'\beta + \mu_i + v_{it}, \text{for } i = 1, \ldots, n; t = 1, \ldots, T \tag{10}$$

Baltagi et al. (2012) proposes a simple asymptotic bias correction for

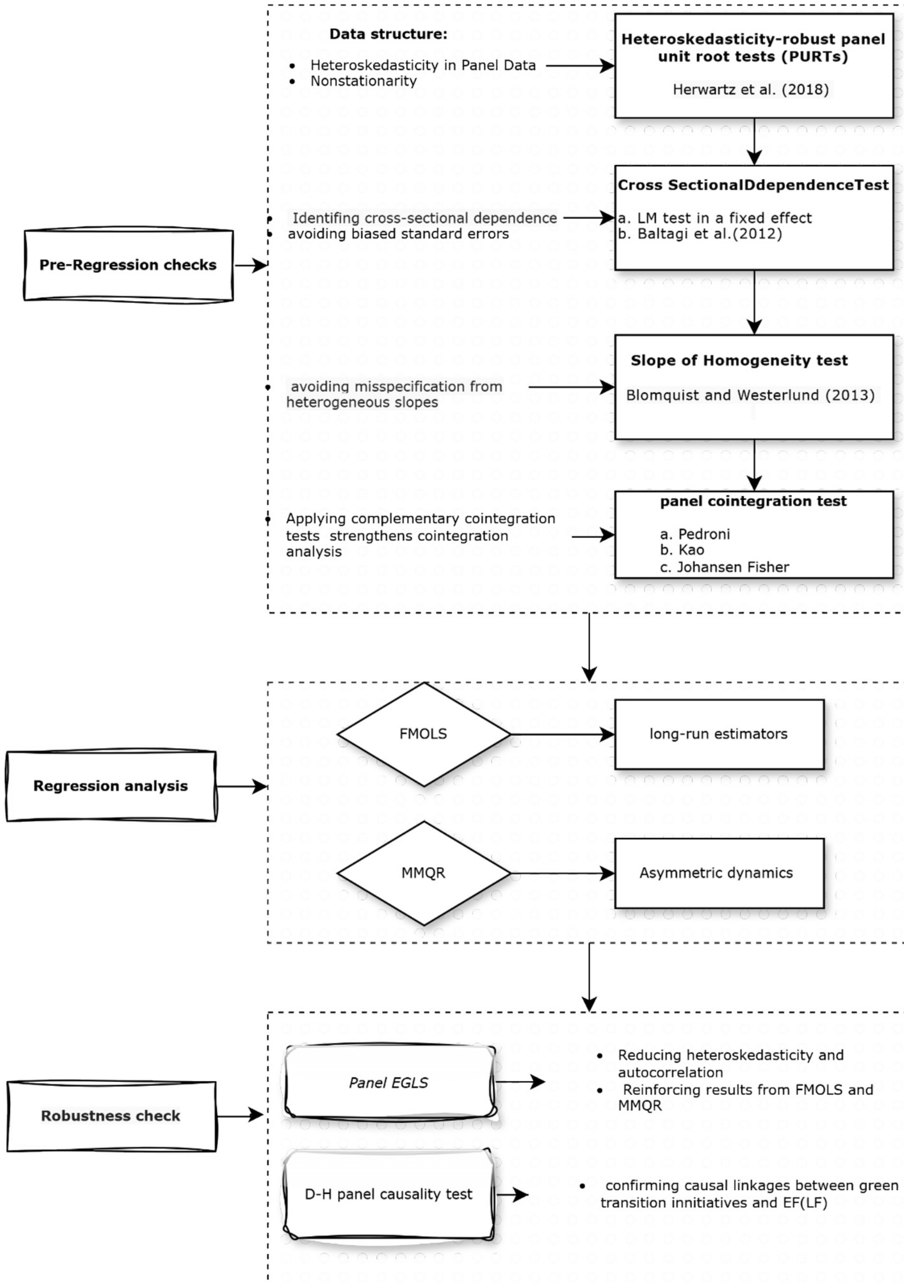

Fig. 5. The procedures of econometric strategies.

the scaled Lagrange multiplier (LM) test, as shown in Eq. (11):

$$LM_{BC} = LM_P - \frac{n}{2(T-1)}$$

$$= \sqrt{\frac{1}{n(n-1)}}\sum_{i=1}^{n-1}\sum_{j=i+1}^{n}\left(T\widehat{\rho}_{ij}^{2}-1\right) - \frac{n}{2(T-1)} \tag{11}$$

Furthermore, the slope homogeneity test relies on the delta tildes ($\widetilde{\Delta}$) and adjusted delta tildes ($\widetilde{\Delta}_{adj}$)

$$\widetilde{\Delta} = (N)^{\frac{1}{2}}(2K)^{-\frac{1}{2}}\left(\frac{1}{N}\widetilde{S} - K\right) \tag{12}$$

$$\widetilde{\Delta}_{adj} = (N)^{\frac{1}{2}}\left(\frac{2K(T-K-1)}{T+1}\right)^{-\frac{1}{2}}\left(\frac{1}{N}\widetilde{S} - 2K\right) \tag{13}$$

Blomquist and Westerlund (2013) introduce a heteroskedasticity-robust function of Δ_{HAC}, which is given by Eqs. (14) and (15).

$$\Delta_{HAC} = \sqrt{N}\left(\frac{N^{-1}S_{HAC} - k}{\sqrt{2k}}\right), \tag{14}$$

Where,

$$S_{HAC} = \sum^{N} T(\widehat{\beta}_i - \widehat{\beta})'\left(\widehat{Q}_{i,T}\widehat{V}_{i,T}^{-1}\widehat{Q}_{i,T}\right)(\widehat{\beta}_i - \widehat{\beta}) \tag{15}$$

4.3. Fully modified ordinary least squares (FMOLS)

The FMOLS estimation process involves a comprehensive asymptotic ordinary mix. This process enables the use of standard Wald tests by leveraging the asymptotic inference derived from the Chi-square distribution. The estimator, denoted as $\widehat{\theta}$, is presented in Eq. (16).

$$\widehat{\theta} = \begin{bmatrix} \beta \\ \widehat{\gamma}_1 \end{bmatrix} = \left(\sum_{t=2}^{T} Z_t Z_t' \right)^{-1} \left(\sum_{t=2}^{T} Z_t \vartheta_t^{+} - T \begin{bmatrix} \boldsymbol{X}_{12}^{+} \\ 0 \end{bmatrix} \right) \tag{16}$$

Where the symbol ϑ is followed by the regressors $\boldsymbol{X}$, while $\widehat{\Omega}$ and $\widehat{\lambda}$ represent covariance matrices. These matrices are constructed using residuals, which can be shown by eqs. (17)–(19):

$$\vartheta_t^{+} = \vartheta_t - \widehat{\omega}_{12}\widehat{\Omega}_{22}^{-1}\widehat{u}_2 \tag{17}$$

$$\widehat{\lambda}_{12}^{+} = \widehat{\lambda}_{12} - \widehat{\omega}_{12}\widehat{\Omega}_{22}^{-1}\lambda_{22} \tag{18}$$

$$Z_t = \left(X_t', D_t'\right) \tag{19}$$

Then, Eq. (20) provides the specific formula or method for calculating the estimator $\widehat{\omega}_{1.2}$

$$\widehat{\omega}_{1.2} = \widehat{\omega}_{11} - \widehat{\omega}_{12}\widehat{\Omega}_{22}^{-1}\widehat{\omega}_{21} \tag{20}$$

Nguyen et al. (2021) emphasized the capacity of FMOLS to address dynamic heterogeneity inherent in heterogeneous cross-sectional dimensions.

4.4. Method of moments quantile regression (MMQR)

This work uses the MMQR proposed by Machado and Silva (2019) to investigate heterogeneity and asymmetric effects across quantiles. This approach involves utilizing generalized median regression estimation, which takes into account different quantiles. Given X_{it}, the conditional quantile of Y_{it} is expressed in Eq. (21):

$$Y_{it} = \alpha_i + X_{it} + (\lambda_i + Z_i\Psi)U_{it} i = 1, 2, \dots .n \tag{21}$$

Here, $\lambda_i + Z_i\Psi > 0$ indicates the probability, and $\{\alpha_i, \lambda_i, \Psi\}$ represents the parameters to be estimated for the fixed effects. Z_i is a k-vector, and U_{it} is identically distributed. Eq. (22) is formulated with fixed-effects specifications.

$$Q_y(\delta|X_{it}) = (\alpha_i + \lambda_i q(\delta)\,) + X_{it}\Phi + Z_{it}\Psi q(\delta) \tag{22}$$

In this equation, X_{it} denotes the independent variables employed in this work, Q_y represents the quantiles of Y_{it}, and $\alpha_i + \lambda_i q(\delta)$ indicates the fixed effect across quantiles of $q(\delta)$.

Following Machado and Silva (2019), $q(\tau) = F_U^{-1}(\tau)$ is used to address optimization issues from the quantiles, and this process is given by Eq. (23):

$$\text{Min } q = \Sigma_i \Sigma t \eta \left[R_{it} - \left(\lambda_i + Z_{i\gamma}\right) q\right] \tag{23}$$

Here, $\eta_\delta R_{it} = (\delta - 1)RI\{R \le 0\} + \text{TRI}\{R > 0\}$ indicates the analyzed check function.

In this study, the dependent variables are EF and LF. Equations for quantiles such as 25th, 50th, 75th and 95th are provided in Eqs. (24) to (27).

$$Q_{0.25}\left(\frac{EF}{LF_{it}}\right) = \&\lambda_{0.25} + \beta_{1,0.25}GDP_{it} + \beta_{2,0.25}NRS_{\text{it}} + \beta_{3,0.25}POP_{it}$$

$$+\beta_{4,0.25}GT_{it} + \beta_{5,0.25}RES_{it} + \beta_{6,0.25}GFC_{it} + \mu_{0.25,it} \tag{24}$$

$$Q_{0.5}\left(\frac{EF}{LF_{it}}\right) = \&\lambda_{0.5} + \beta_{1,0.5}GDP_{it} + \beta_{2,0.5}NRS_{\text{it}} + \beta_{3,0.5}POP_{it}$$

$$+\beta_{4,0.5}GT_{it} + \beta_{5,0.5}RES_{it} + \beta_{6,0.5}GFC_{it} + \mu_{0.5,it} \tag{25}$$

$$Q_{0.75}\left(\frac{EF}{LF_{it}}\right) = \&\lambda_{0.75} + \beta_{1,0.75}GDP_{it} + \beta_{2,0.75}NRS_{\text{it}} + \beta_{3,0.75}POP_{it}$$

$$+\beta_{4,0.75}GT_{it} + \beta_{5,0.75}RES_{it} + \beta_{6,0.75}GFC_{it} + \mu_{0.75,it} \tag{26}$$

$$Q_{0.95}\left(\frac{EF}{LF_{it}}\right) = \&\lambda_{0.95} + \beta_{1,0.95}GDP_{it} + \beta_{2,0.95}NRS_{\text{it}} + \beta_{3,0.95}POP_{it}$$

$$+\beta_{4,0.95}GT_{it} + \beta_{5,0.95}RES_{it} + \beta_{6,0.95}GFC_{it} + \mu_{0.95,it} \tag{27}$$

4.5. Data

Table 1 presents the data sources, measurement methods, and multidimensional indicators used to capture the complexity of the G-6 countries' green transitions and the economy-resources-population dynamics.

Formal normality tests, including the Shapiro-Wilk test and the Lilliefors test (an enhanced method of the Kolmogorov-Smirnov test), were conducted on the log-transformed variables. However, the tests failed to validate normal distribution (see Table 2). Fig. 6 presents Q-Q plots to assess the normality of the first-lag difference variables. The quantiles of the observed variables are plotted against the theoretical quantiles of a normal distribution. The Q-Q plots indicate that the data points largely align with a diagonal line, suggesting an approximate normal distribution. These results validate the suitability of the MMQR method, which is particularly well-suited for the panel dataset (Zhang et al., 2024; Shayanmehr et al., 2023).

Fig. 7a and b use chord graphs to visualize how variables interact differently across the six countries analyzed here. Thicker chords signify stronger correlations, whereas thinner chords represent weaker correlations. GDP and NRS are closely connected, particularly in countries with higher population density (e.g., the USA). POP significantly impacts NRS, emphasizing how demographic pressures affect sustainability. The graphs also reveal strong linkages between RES, GFC, and GT, with a notable correlation between RES and GFC. Environmental degradation is closely linked to GT, GFC, and RES, suggesting that green transitions play a key role in improving environmental sustainability.

The chord graphs display significant heterogeneity among variables and emphasize the importance of conducting multicollinearity tests when using long-run cointegration models to ensure the robustness of the empirical analysis.

Table 1
Data measurements and sources.

Variables	Measurement	Source
EF	Ecological footprint (gha per person)	Global Footprint Network
LF	Load capacity factor (Global hectares per capita)	Global Footprint Network
GDP	GDP per capita (GDP per capita (constant 2017 international $)	WDI
RES	Renewable energy consumption (% of total final energy consumption)	WDI
POP	Population density(Inhabitants per square kilometer)	OECD
NRS	Natural resources rents (% of gdp)	WDI
GF	Green finance (Percentage of government allocations for environmental R&D)	OECD
GT	Development of environment-related technologies, % all technologies	OECD

Table 2
The results of normality tests.

Variables	Shapiro-Wilk test		Lilliefors Test	
	Statistics	*P*-value	Statistics	P-value
LNLF	0.923	0.000	0.129	0.001
LNEF	0.796	0.000	0.261	0.000
LNGDP	0.943	0.000	0.131	0.000
LNNRS	0.747	0.000	0.291	0.000
LNRES	0.913	0.000	0.143	0.000
LNGFC	0.938	0.000	0.128	0.000
LNGT	0.851	0.000	0.151	0.000

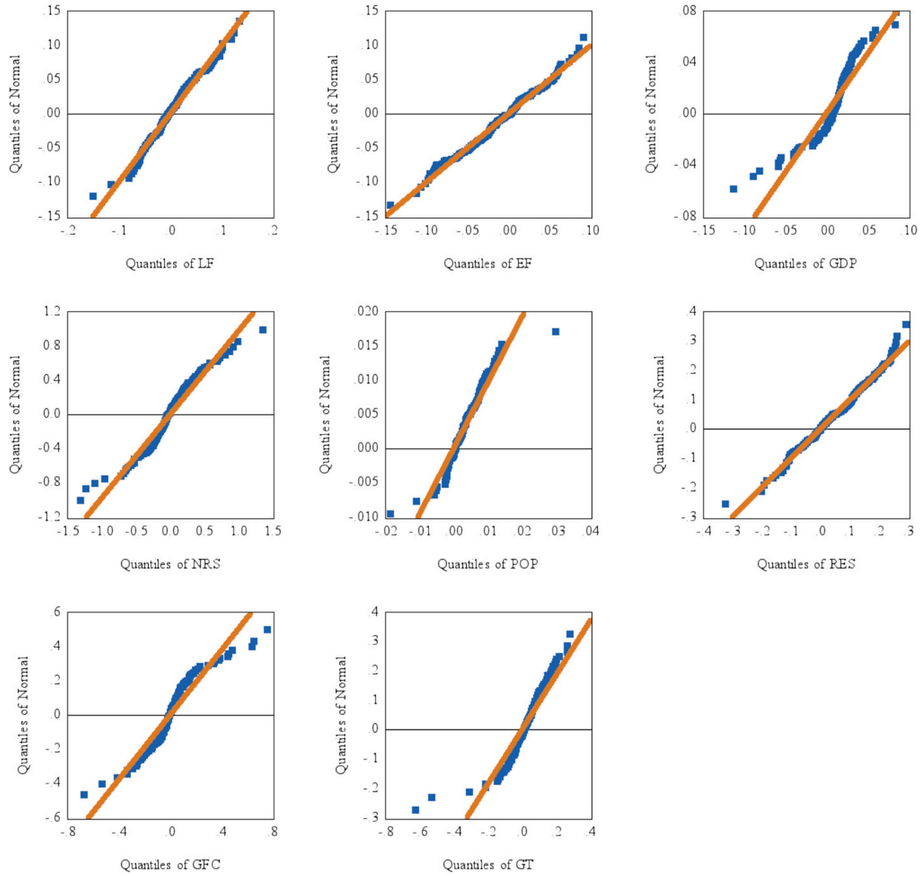

Fig. 6. Q-Q plots.

5. Empirical results and discussion

5.1. Panel unit root, CD and slope heterogeneity test results

In this empirical investigation, we begin the analysis by examining the stationarity properties of the first difference of the natural logarithm-transformed variables for the G6 economies, and the results of which are reported in Table 3. The estimates of *t_hs and t_dh* reveal the presence of a unit root in all variables, suggesting that the variables are non-stationary in their level form but achieve stationarity in the first difference. Thus, the variables are categorized as integrated of order 1. These empirical outcomes establish the foundation for the application of panel cointegration techniques in subsequent analyses.

After confirming the stationarity properties of the variables, we proceed to investigate the presence of CD utilizing four diagnostic tests. The results are shown in Table 4, demonstrating that CD is confirmed for all variables at a 1 % significance level. Notably, the results reveal the presence of cross-sectional fixed effects for model 1 and 2, as evidenced by the LM test proposed by Baltagi et al. (2012). This evidence serves as critical evidence for interpreting the subsequent regression estimation. Specifically, it is important to recognize that ignoring CD in estimation could lead to several consequences, including a potential loss in estimator efficiency due to unaccounted residual dependence. Therefore, the cointegration methods employed in this analysis are chosen to mitigate biased results based on these test results.

After conducting the CD test, the results of the Blomquist and Westerlund, 2013 test for slope heterogeneity are presented in Table 5, revealing that the slope parameters exhibit standardization and homogeneity. We further use a bootstrap-based test that accounts for heteroscedastic and autocorrelation consistent (HAC) standard errors. The results provide evidence against the null hypothesis of homogeneous slope coefficients at the 5 % significance level, indicating that the slope parameters are heterogeneous across the panel.

5.2. Panel cointegration test

After confirming that panel data series are integrated of order 1 and stationary, strong evidence was found to validate the results of CD and slope homogeneity tests. Two notable panel cointegration tests are applied: the Pedroni Residual Cointegration Test (Table 6 panel a) and the KAO Residual Cointegration Test (Table 6 panel b). The results provide insights into the cointegration properties of the panel data. Additionally, we conducted the Johansen Fisher Panel Cointegration Test to provide individual cross-section results for each country (Table 3c), enhancing the novel insights of this study and reducing the risk of biased results. The outcomes indicate that the panel data series converge in the long run, leading to the rejection of the null hypothesis of no long-term convergence among the series.

5.3. FMOLS results

After conducting tests for non-stationarity, cross-sectional dependence, slope heterogeneity, and panel cointegration for model 1 and model 2, we could confirm that the long-run coefficients estimate, which sever the synergistic effects in this study, are robust and reliable. Table 7 panel a presents the long-run impact of GDP, NRS, POP, RES, GFC, and GT on LF (model 1) and EF (model2).

5.3.1. GDP, NRS, POP and environmental degradation

Economic expansion and natural resource depletion are significant drivers of ecological degradation. Specifically, a 1 % increase in real income correlates with a 0.558 % reduction in LF and a 0.726 % increase

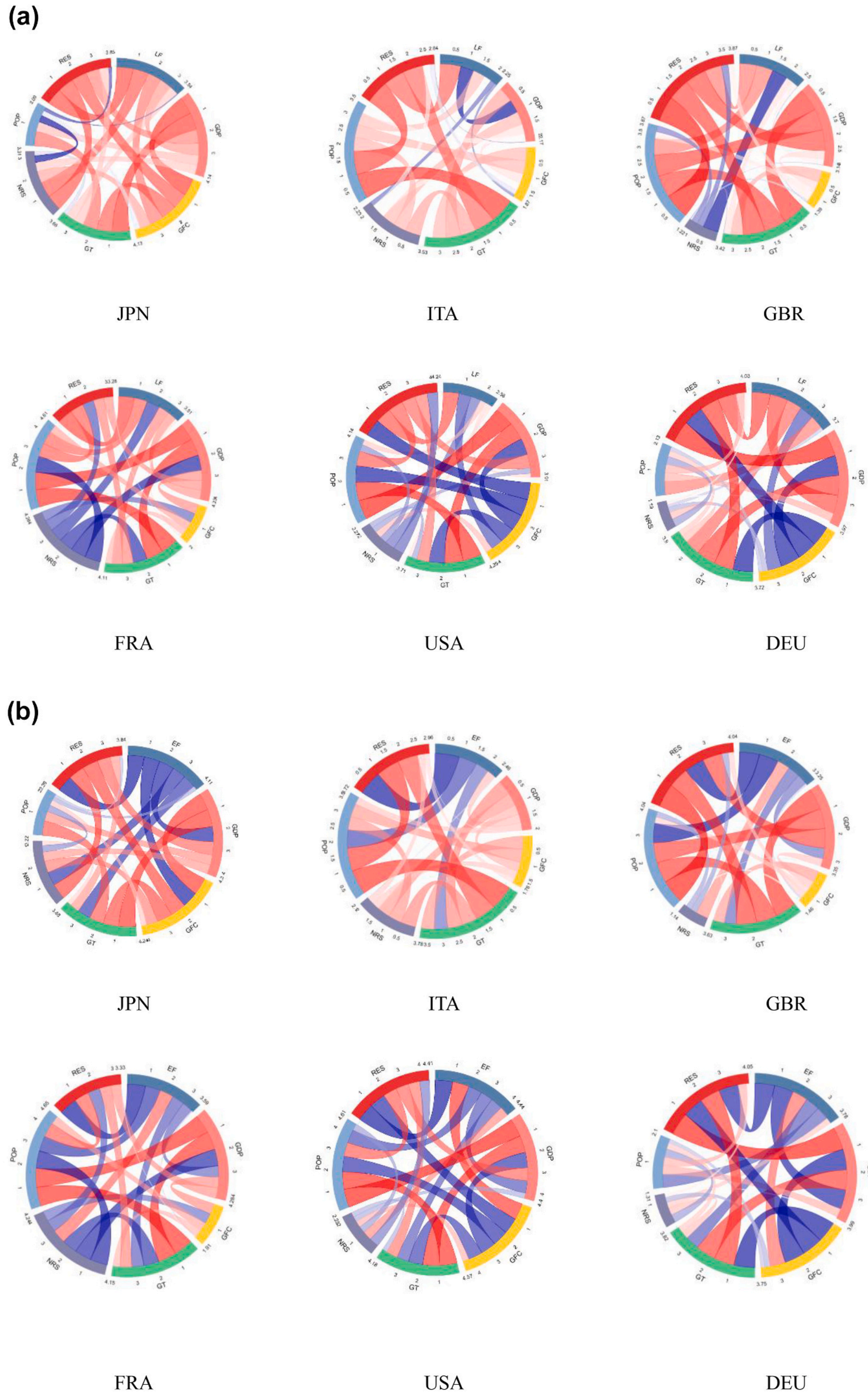

Fig. 7. a. Chord graph showing correlations between LF and its drivers for G-6 economies.
b. Chord graph showing correlations between EF and its drivers for G-6 economies.

in EF, indicating that economic growth tends to reduce ecological sustainability. This finding aligns with Sun et al. (2024b), which confirm that economic growth intensifies the pressure on both renewable and non-renewable energy use, thereby stressing environmental impacts. In G6 countries, a 1 % increase in NRS results in a 0.032 % decline in LF and a 0.022 % increase in EF. These findings are consistent with the findings of Uche et al. (2024), which indicate that both resource utilization and economic expansion contribute substantially to environmental degradation. Finally, a 1 % increase in POP leads to a 1.648 % decrease in EF and a 0.648 % increase in LF. The result is consistent with Sarkodie (2021), which suggested that higher POP can increase natural resource demands through extraction or imports while promoting sustainable urban practices and efficient resource use.

5.3.2. *Green transition and environmental degradation*

The elasticity coefficients of RES are the highest among the three key indicators analyzed, at 0.117 % and 0.139 %, highlighting the substantial influence on both LF and EF. The coefficients indicate that increasing the share of renewables in the energy mix has contributed to improving LF and reducing EF in G-6 countries. GFC also plays an

Table 3
Panel unit root tests test.

Variables	Name	Statistic	p-value	constant
EF	t_hs	−2.495	0.006	constant
	t_dh	−2.740	0.003	
LF	t_hs	−2.082	0.019	no constant
	t_dh	−1.849	0.032	
GDP	t_hs	−2.462	0.007	no constant
	t_dh	−2.359	0.009	
NRS	t_hs	−2.244	0.012	constant
	t_dh	−2.068	0.019	
POP	t_hs	−2.189	0.014	no constant
	t_dh	−1.444	0.074	
RES	t_hs	−1.917	0.028	constant
	t_dh	−2.056	0.020	
GFC	t_hs	−3.102	0.001	constant
	t_dh	−2.799	0.003	
GT	t_hs	−2.656	0.004	no constant
	t_dh	−1.295	0.098	

Table 4
CD dependence test results.

Test	Statistic	Prob.	Statistic	Prob.
	Model1		Model2	
Breusch-Pagan LM	66.705	0.000	123.112	0.000
Pesaran scaled	9.440	0.000	19.738	0.000
Baltagi et al. (2012) LM	9.343	0.000	19.642	0.000
Pesaran CD	4.631	0.000	8.069	0.000

Table 5
Results of slope heterogeneity test (Blomquist and Westerlund (2013)).

H_0: slope coefficients are homogenous		
model1	Delta	p-value
$\widetilde{\Delta}$	−2.335	0.02
$\widetilde{\Delta}_{adj.}$	−2.791	0.005
model 2	Delta	p-value
$\widetilde{\Delta}$	−2.522	0.012
$\widetilde{\Delta}_{adj.}$	−3.014	0.003

essential role in reducing ecological degradation. A 1 % increase leads to a 0.041 % improvement in LF and a 0.055 % reduction in EF. This reaffirms its importance in advancing environmental sustainability in developed countries (Deng et al., 2024). GFC accelerates the transition by funding sustainable projects such as renewable energy and energy efficiency initiatives. GT exhibits a positive long-term impact on LF. A 1 % increase in GT corresponds to a 0.018 % rise in LF and a 0.035 % reduction in EF. The results demonstrate the critical role of GT in promoting cleaner production and combating environmental degradation. The widespread adoption of eco-technologies is closely linked to the international environmental treaties and protocols, especially post-1990, which marks the starting point of this study (Sun et al., 2024b). As proposed by Montenegro et al. (2021), the development of GT correlates with the distinct technological pathways. GT mitigates environmental risks by improving pollution control and waste management, thus reducing ecosystem impacts.

The interaction of RES, GFC and GT creates a synergistic governance framework that amplifies their individual impacts. GFC supports the development and deployment of GT, while GT optimizes the performance of RES projects. The RES accelerates the adoption of renewables, enhancing energy efficiency and further reducing ecological degradation. This synergy could promote sustained ecological recovery, decreased degradation, and long-term ecological sustainability.

5.4. MMQR results

Fig. 8a and b visualize the empirical results derived from the MMQR estimation, examining the dynamics between LF (model 1), EF (model 2), and impact factors in G6 countries over the past three decades.

5.4.1. GDP, NRS, POP and environmental degradation

GDP and NRS exert significant negative effects on LF in G6 economies. Specifically, GDP strongly reduces LF. For instance, at the analyzed location coefficient, a 1 % increase in GDP growth corresponds to a 0.543 % decline in LF, while increasing the EF by 0.72 %. Across all quantiles, the negative effect of GDP on LF ranges from −0.52 % to −0.57 %, and its effect on EF varies from −0.71 % to −0.73 %. This progression across quantiles indicates that the impacts of environmental degradation intensify with higher GDP, reinforcing prior findings that identify economic expansion as a consistent contributor to degradation. Regarding NRS, a 1 % increase in NRS results in a 0.035 % decline in LF. This negative effect is more pronounced at lower quantiles (qtile_5 to qtile_30). In contrast, EF rises by 0.024 % with a 1 % increase in NRS. This positive effect amplifies at higher quantiles, especially between the qtile_80 and qtile_95th. For example, at the qtile_95, a 1 % increase in NRS leads to a 0.046 % rise in EF, while a 0.007 % decrease in LF. POP presents the positive effects on environmental degradation peak at the qtile_95, where a 1 % increase in POP is associated with a 1.05 % improvement in LF, while decreasing EF by 1.239 %.

5.4.2. Green transition and environmental degradation

Table 8 presents RES positively influence LF and negatively impact EF across the entire quantile distribution. Specifically, the positive effect of RES on LF remains consistent at approximately 0.12 % across all quantiles, while the negative impact on EF ranges from −0.13 % to −0.15 %. This consistency reveals the role of RES in fostering a reliable and adaptable energy system, increasingly critical because of intensifying climate crisis. From an adaptation perspective, RES enhances energy security and resilience. GFC also demonstrates positive and statistically significant effect on both LF and EF across the location coefficient and quantiles ranging from the 5th to the 95th quantile (see Fig. 8 and Table 8). Specifically, at the location coefficient, a 1 % increase in GFC is associated with a 0.039 % improvement in LF. The most substantial positive effects are observed at the 95th percentile, where GFC improves LF by 0.078 %. In contrast, the minimal effects are observed at the 5th percentile (0.006 %). EF improves by 0.039 % with a 1 % rise in GFC, peaking at 0.078 % at the qtile_95 and decreasing to 0.006 % at the qtile_5.

GT is identified as a positive driver of LF across most quantiles, though the effect is generally less pronounced compared to RES and GFC. Specifically, GT exhibits significant positive effects in lower to middle quantiles (qtile_5 to qtile_40), with coefficients ranging from 0.02 to 0.06. In the higher quantiles (qtile_80 to qtile_95), GT demonstrates a negative effect on LF, though this effect is not statistically significant. GT significantly reduces the EF in the higher quantiles (qtile_70 to qtile_95). For instance, at the qtile_95 of model 2, a 1 % increase in GT corresponds to a 0.072 % reduction in EF. This weak effect evolution may stem from the relatively immature stage of GT development in some countries (Uche et al., 2024).

The integrated results validate the reliable expansion of the STIRPAT framework, facilitating a comprehensive analysis of adaptation strategies and mitigation efforts, particularly in nonlinear and heterogeneous systems. The long-run elasticity coefficients derived from FMOLS align with STIRPAT's hypotheses regarding the interactions between drivers and environmental degradation. Specifically, the coefficients capture the long-term dynamics between green transition initiatives and environmental degradation. Meanwhile, MMQR enhances the explanatory power of the STIRPAT framework by revealing quantile-specific effects. The findings support the development of country-specific adaptation and mitigation strategies, while highlighting the potential of green

Table 6
Panel cointegration test results.

	model1				model2			
Panel a: Pedroni Residual Cointegration Test								
			Weighted				Weighted	
	Statistic	Prob.	Statistic	Prob.	Statistic	Prob.	Statistic	Prob.
Panel v-Statistic	0.179	0.429	0.170	0.433	−0.027	0.511	−0.957	0.831
Panel rho-Statistic	−0.100	0.460	0.026	0.510	0.151	0.560	0.036	0.514
Panel PP-Statistic	−4.165	0.000	−3.731	0.000	−3.619	0.000	−3.917	0.000
Panel ADF-Statistic	−4.257	0.000	−3.855	0.000	−3.707	0.000	−3.990	0.000
	Statistic	Prob.			Statistic	Prob.		
Group rho-Statistic	0.811	0.791			1.185	0.882		
Group PP-Statistic	−3.757	0.000			−3.356	0.000		
Group ADF-Statistic	−3.804	0.000			−0.896	0.185		
Panel b: KAO Residual Cointegration Test								
	t-Stat.	Prob.			t-Stat.	Prob.		
ADF	−2.546	0.005			−1.302	0.096		
Residual variance	0.000				0.049			
HAC variance	0.000				0.042			
Panel c: Johansen Fisher Panel Cointegration Test: Individual cross section results								
Hypothesis of no cointegration								
	Trace Test		Max-Eign Test		Trace Test		Max-Eign Test	
Cross Section	Statistics	Prob.	Statistics	Prob.	Statistics	Prob.	Statistics	Prob.
JPN	169.576	0.000	54.489	0.005	166.233	0.000	55.179	0.004
DEU	240.168	0.000	86.324	0.000	243.439	0.000	80.216	0.000
USA	174.177	0.000	62.042	0.001	179.289	0.000	61.139	0.001
FRA	231.401	0.000	71.859	0.000	203.574	0.000	62.970	0.000
GBR	220.336	0.000	76.549	0.000	209.157	0.000	72.854	0.000
ITA	190.290	0.000	62.766	0.000	219.355	0.000	68.417	0.000

Table 7
FMOLS results.

	Panel a. Model1: dependent variable = LF				Panel b Model2: dependent variable = EF			
Variable	Coef.	Std. Error	Prob.	VIF[a]	Coef.	Std. Error	Prob.	VIF
GDP	−0.558	0.044	0.000	0.000	0.726	0.047	0.000	0.000
NRS	−0.032	0.006	0.000	0.002	0.022	0.006	0.001	0.002
POP	0.684	0.101	0.000	0.010	−1.648	0.109	0.000	0.012
GT	0.018	0.01	0.059	0.000	−0.035	0.010	0.001	0.000
RES	0.117	0.005	0.000	0.000	−0.139	0.005	0.000	0.000
GFC	0.041	0.007	0.000	0.000	−0.055	0.008	0.000	0.000
R-squared	0.986	S.E. of reg.	0.056		0.947	S.E. of reg.	0.060	

[a] Coefficient variance value.

transitions to synergistically reduce environmental degradation and promote actionable solutions.

6. Robustness analysis

6.1. Panel estimated generalized least squares (EGLS) regression

This study uses an alternative regression method, which proposed by Khan et al. (2022) and Mance et al. (2020). This method is effective in addressing issues commonly encountered in panel data analyses, including heteroskedasticity and autocorrelation. As shown in Table 9, the coefficients obtained from the panel EGLS regression are closely similar with the results from the FMOLS and MMQR location coefficient results. This consistency not only supports the robustness of the prior analyses but also strengthens the reliability of our conclusions. Furthermore, the results of panel EGLS enhances a deeper understanding of the underlying dynamics within the panel data, effectively validating the empirical estimates. Through this robustness analysis, we emphasize the importance of using different regression methods to ensure the empirical evidence is robust and withstands scrutiny. This validation process provides a solid foundation for policy recommendations and future research.

6.2. Heterogeneous panel causality analysis

In contrast to conventional long-term panel estimators, which only capture long-term coefficients, this section further uses the D-H panel causality method to display the causal relationships among green transition indicators, GDP, NRS, and POP on LF and EF. D-H test uses the Wald test statistic to test the causality hypothesis, with the null and alternative hypotheses defined in Eqs. (28) and (29), respectively.

$$X_{it} = \alpha_i + \sum_{j-1}^{J} \beta_i^j X_{i(t-j)} + \sum_{j-1}^{J} \gamma_i^j Z_{i(t-j)} + \mu_{it} \tag{28}$$

$$H_0 : \mu_i = 0 \text{ for} \forall i$$

$$H_1 : \begin{cases} \mu_i = 0 \text{ for all } i = 1, 2, 3, 4 \cdots\cdots\cdots\cdots, N_1 \\ \mu_i \neq 0 \text{ for all } i = N_1 + 1, 2, 3, 4, \cdots\cdots N \end{cases}$$

$$W_{N.T}^{HNC} = N^{-1} \sum_{i=1}^{N} W_{i,T} \tag{29}$$

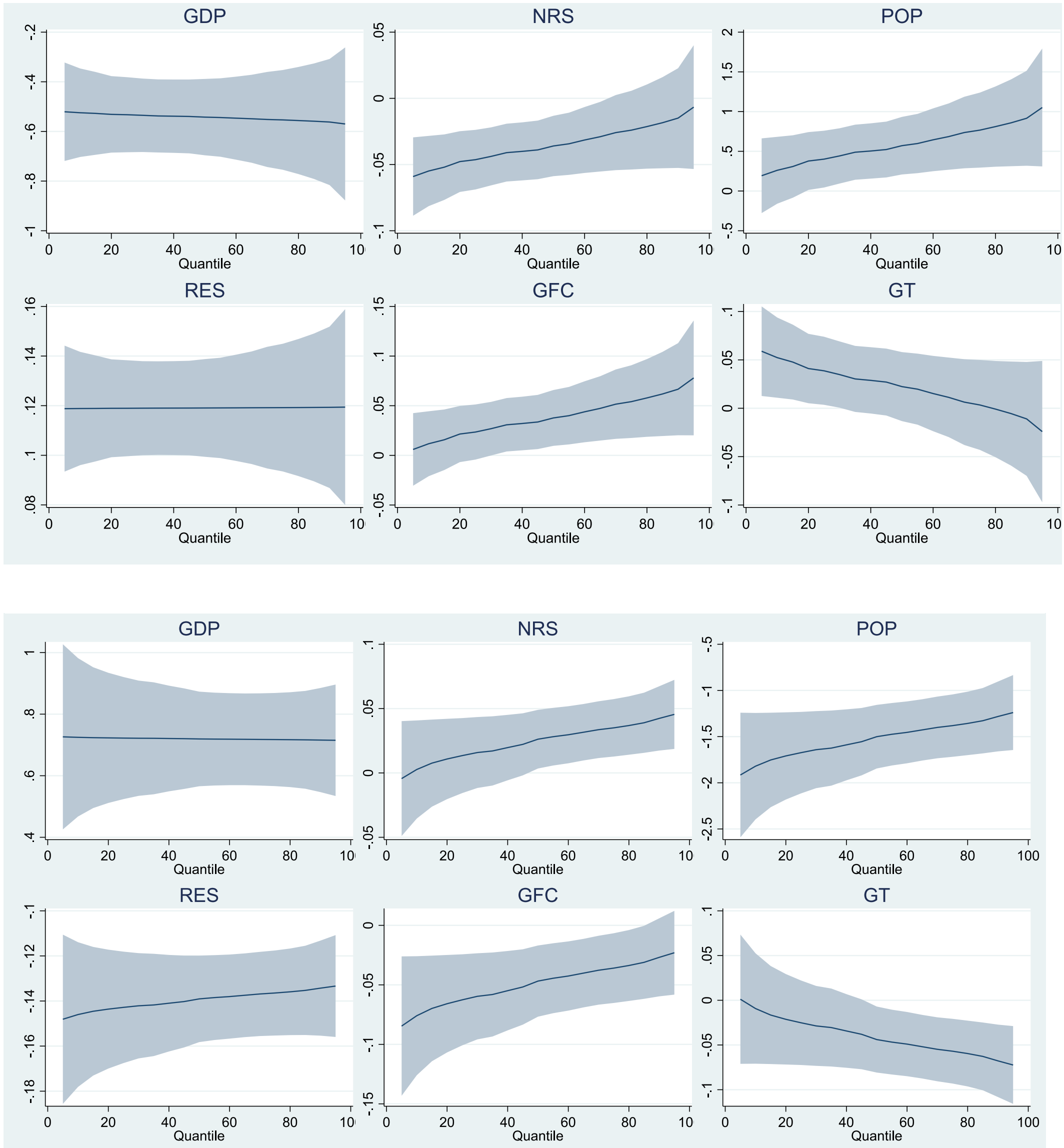

Fig. 8. a. MMQR results for model 1.
b. MMQR results for model 2.

Where X_{it} and Z_{it} represent the dependent and independent variables, respectively. The long-run elasticity and autoregressive parameters are denoted by β_i^j and γ_i^j.

As shown in Fig. 9 and Table 10, D-H robustness check reinforces the reliability and validity of the results. The detection of both bidirectional and unidirectional causalities across different variables strengthens the argument that the observed interactions are not spurious but rather reflect the dynamics within the system. Moreover, the unidirectional causality from GDP, GFC, and RES towards both LF and EF provides additional confirmation of the robustness of the results. The consistent causal effects of these variables on both LF and EF reconfirms the importance in shaping the energy system's capacity to meet demand and the environmental sustainability of economic activities. Finally, the bidirectional causality between GT, NRS, and POP on both LF and EF adds another argument of the robustness. The persistence of these causal relationships, even under varying conditions and potential confounding factors, indicating that the observed interactions are robust and should be considered in policy formulation.

7. Conclusions, implications and limitations

7.1. Conclusions

This study integrates EF and LF to address the limitations of CO_2-centric analyses of environmental degradation, providing empirical frameworks to reveal adaptation, mitigation, and synergistic effects of green transition initiatives in G-6 economies. From this work, several specific conclusions can be obtained: (i) The long-term dynamics of economic expansion, resource depletion, and population density are characterized by complex interactions that contribute to environmental degradation. Addressing these challenges requires adaptive and mitigation strategies that navigate the trade-offs between socio-economic development and ecological thresholds. (ii) The synergistic effects of RES, GFC, and GT are suggested as actionable, adaptable, and scalable policy pathways to mitigate environmental degradation. The combined effect of components amplifies their cumulative impact, accelerating progress towards green transition. (iii) MMQR reveals asymmetric dynamics between environmental degradation and green transitions. RES consistently mitigate environmental degradation across all quantiles. A

Table 8
MMQR results.

Model1			Quantile Grids									
variables	location		qtile_15		qtile_35		qtile_55		qtile_75		qtile_95	
	coef.	p-value	coef.	p-value	coef.	p-value	coef.	p-value	coef.	p-value	coef.	p-value
GDP	−0.543	0.000	−0.527	0.000	−0.538	0.000	−0.544	0.000	−0.553	0.000	−0.570	0.000
NRS	−0.035	0.003	−0.052	0.000	−0.041	0.000	−0.034	0.004	−0.024	0.113	−0.007	0.781
POP	0.589	0.002	0.309	0.123	0.489	0.006	0.598	0.002	0.767	0.001	1.052	0.005
RES	0.119	0.000	0.119	0.000	0.119	0.000	0.119	0.000	0.119	0.000	0.119	0.000
GFC	0.039	0.007	0.016	0.312	0.031	0.025	0.040	0.007	0.054	0.004	0.078	0.008
GT	0.021	0.265	0.048	0.016	0.030	0.082	0.020	0.292	0.003	0.885	−0.024	0.517
_cons	1.311	0.245	2.581	0.032	1.766	0.096	1.272	0.266	0.509	0.726	−0.780	0.729
							Quantile Grids					
Model2	location		qtile_15		qtile_35		qtile_55		qtile_75		qtile_95	
	coef.	p-value	coef.	p-value	coef.	p-value	coef.	p-value	coef.	p-value	coef.	p-value
GDP	0.720	0.000	0.724	0.000	0.722	0.000	0.719	0.000	0.718	0.000	0.715	0.000
NRS	0.024	0.045	0.008	0.659	0.017	0.213	0.028	0.014	0.035	0.002	0.046	0.001
POP	−1.532	0.000	−1.753	0.000	−1.624	0.000	−1.474	0.000	−1.381	0.000	−1.239	0.000
RES	−0.140	0.000	−0.145	0.000	−0.142	0.000	−0.138	0.000	−0.136	0.000	−0.133	0.000
GFC	−0.050	0.001	−0.070	0.002	−0.058	0.001	−0.044	0.003	−0.036	0.016	−0.023	0.200
GT	−0.040	0.036	−0.017	0.555	−0.030	0.170	−0.047	0.011	−0.057	0.002	−0.072	0.001
_cons	1.939	0.076	3.031	0.055	2.395	0.057	1.652	0.114	1.190	0.255	0.488	0.697

Table 9
The results of panel EGLS.

Panel a. Model1				
Variable	Coef.	Std.	t-Stat.	Prob.
GDP	−0.479	0.081	−5.908	0.000
NRS	−0.032	0.011	−2.951	0.004
POP	0.347	0.168	2.066	0.040
GT	0.046	0.019	2.425	0.016
RES	0.097	0.009	10.771	0.000
GFC	0.029	0.012	2.348	0.020
C	1.990	1.000	1.990	0.048
Panel b. Model2				
Variable	Coef.	Std.	t-Stat.	Prob.
GDP	0.599	0.082	7.279	0.000
NRS	0.020	0.011	1.770	0.078
POP	−1.091	0.166	−6.562	0.000
GT	−0.084	0.020	−4.190	0.000
RES	−0.098	0.009	−10.660	0.000
GFC	−0.030	0.012	−2.503	0.013
C	0.739	1.002	0.738	0.462

1 % increase in RES reduces the EF by 0.13–0.15 % and improves the LF by 0.12 %, establishing energy transition as a critical cornerstone of effective mitigation and adaption. GFC presents escalating benefits at higher percentiles (qtile_95). The scalability limitations of GT at upper quantiles and the diminishing marginal returns in ecological restoration suggest a threshold beyond which the effectiveness of GT may decline. (iv) The robustness check of alternative regression of Panel EGLS and D-H causality tests validate empirical findings, ensuring conclusions reliably capture the complex interactions among variables influencing environmental degradation.

7.2. Implications

The study emphasizes the alignment of green transition initiatives with the SDGs, particularly SDG 7 (Affordable and Clean Energy), SDG 11 (Sustainable Cities and Communities), and SDG 13 (Climate Action). It also provides insights into advancing environmental sustainability through green transitions.

(i) Policymakers can leverage an expanded STIRPAT framework to demonstrate the long-term impacts of green transition policies, ensuring environmental and economic growth goals are achieved in tandem. The study also highlights the need to integrate broader environmental metrics (e.g., resource efficiency, waste management, and land use) to advance SDG 12 (Responsible Consumption and Production). These findings offer a foundation for policies that embed sustainable practices into development strategies, fostering environmental sustainability.
(ii) This work emphasizes the importance of designing green transition policies as actionable, adaptable, and scalable tools capable of supporting environmental sustainability and resource security. For example, policies promoting green innovation and renewable energy adoption directly advance SDG 7, while measures targeting emissions reductions and climate resilience align with SDG 13. Synergies between these initiatives can further amplify progress across multiple SDGs.
(iii) High-income nations, particularly the G-6 have the opportunity to promote clean technology transfers and global clean energy adoption to support SDGs 7 and 13. Emerging economies can address local challenges like energy infrastructure gaps and market inefficiencies to ensure equitable transitions. Additionally, financial tools (e.g., green bonds, tax incentives, and Renewable Energy Investment Trusts) should be embedded in policies to attract private capital and scale green projects.
(iv) Countries like the BRICS should prioritize investments in renewable infrastructure, green innovation, and sustainable resource management. Policymakers in these nations can develop strategies to reduce fossil fuel dependency while promoting resource stewardship. In this context, platforms like the UNFCCC

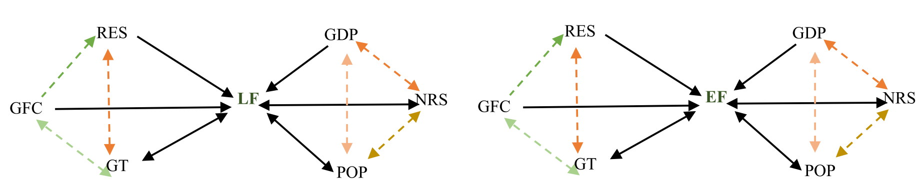

Fig. 9. Results of D-H panel causality test.

Table 10
pairwise causality test results between environmental degradation and key drivers.

Null Hypothesis:	W-Stat.	Zbar-Stat.	Prob.
GDP does not homogeneously cause LF	6.157	7.704	0.000
LF does not homogeneously cause GDP	0.740	−0.511	0.609
GFC does not homogeneously cause LF	3.626	3.866	0.000
LF does not homogeneously cause GFC	1.287	0.318	0.751
GT does not homogeneously cause LF	3.482	3.646	0.000
LF does not homogeneously cause GT	8.185	10.779	0.000
NRS does not homogeneously cause LF	2.290	1.840	0.066
LF does not homogeneously cause NRS	2.664	2.407	0.016
POP does not homogeneously cause LF	2.549	2.232	0.026
LF does not homogeneously cause POP	32.305	47.352	0.000
RES does not homogeneously cause LF	7.256	9.369	0.000
LF does not homogeneously cause RES	1.126	0.073	0.942
GDP does not homogeneously cause EF	7.688	10.025	0.000
EF does not homogeneously cause GDP	0.919	−0.239	0.811
GFC does not homogeneously cause EF	3.639	3.885	0.000
EF does not homogeneously cause GFC	0.947	−0.198	0.843
GT does not homogeneously cause EF	4.365	4.986	0.000
EF does not homogeneously cause GT	8.543	11.322	0.000
NRS does not homogeneously cause EF	3.852	4.208	0.000
EF does not homogeneously cause NRS	2.331	1.902	0.057
POP does not homogeneously cause EF	3.974	4.393	0.000
EF does not homogeneously cause POP	32.444	47.563	0.000
RES does not homogeneously cause EF	6.046	7.535	0.000
EF does not homogeneously cause RES	1.261	0.279	0.780

and the One Belt One Road Initiative can foster global collaboration and resource-sharing, accelerating renewable energy deployment and technological innovation. These efforts will mitigate environmental degradation, drive green growth, and accelerate SDGs achievement.

These implications offer policymakers a cohesive roadmap to integrate energy, urban development, and climate goals, accelerating climate action and environmental sustainability.

7.3. Limitations

The study has several limitations, primarily due to the availability of recent datasets, which may affect the estimation results. There is also an urgent need to establish standardized green transition indicators for better international comparisons and coordinate global efforts. Additionally, the panel regression results may be influenced by socio-economic and environmental contexts across countries. Future studies can discuss specific challenges of green transition by each country. Finally, issues such as omitted variable bias and endogeneity may not have been fully addressed.

Funding

This work received support from the Humanities and Social Science Fund of the Ministry of Education of China [Grant Number: 23YJC850005], the Austrian Science Fund (FWF) [10.55776/ESP1514224] and the Federal Ministry of Education, Science and Research (BMBWF) through Austria's Agency for Education and Internationalization (OeAD) [CZ 13/2024 and PL 12/2024].

CRediT authorship contribution statement

Binlin Li: Conceptualization, Methodology, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Visualization. **Mohammad Mafizur Rahman:** Formal analysis, Investigation, Data curation, Writing – review & editing. **Nils Haneklaus:** Formal analysis, Investigation, Data curation, Writing – review & editing. **Shuqin Li:** Validation, Formal analysis, Investigation, Data curation, Writing – review & editing. **Yufei Zhou:** Validation, Formal analysis, Investigation, Data curation, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

References

Adebayo, T.S., Samour, A., 2024. Renewable energy, fiscal policy and load capacity factor in BRICS countries: novel findings from panel nonlinear ARDL model. Environ. Dev. Sustain. 26, 4365–4389. https://doi.org/10.1007/s10668-022-02888-1.

Anu, Singh A.K., Raza, S.A., Nakonieczny, J., Shahzad, U., 2023. Role of financial inclusion, green innovation, and energy efficiency for environmental performance? Evidence from developed and emerging economies in the lens of sustainable development. Struct. Chang. Econ. Dyn. 64, 213–224. https://doi.org/10.1016/j.strueco.2022.12.008.

Baltagi, B.H., Feng, Q., Kao, C., 2012. A Lagrange multiplier test for cross-sectional dependence in a fixed effects panel data model. J. Econ. 170, 164–177. https://doi.org/10.1016/j.jeconom.2012.04.004.

Blomquist, J., Westerlund, J., 2013. Testing slope homogeneity in large panels with serial correlation. Econ. Lett. 121, 374–378. https://doi.org/10.1016/j.econlet.2013.09.012.

Breitung, J., 2005. A parametric approach to the estimation of Cointegration vectors in panel data. Econ. Rev. 24, 151–173. https://doi.org/10.1081/ETC-200067895.

Dam, M.M., Sarkodie, S.A., 2023. Renewable energy consumption, real income, trade openness, and inverted load capacity factor nexus in Turkiye: revisiting the EKC hypothesis with environmental sustainability. Sustain. Horizons 8, 100063. https://doi.org/10.1016/j.horiz.2023.100063.

Dam, M.M., Durmaz, A., Bekun, F.V., Tiwari, A.K., 2024. The role of green growth and institutional quality on environmental sustainability: a comparison of CO2 emissions, ecological footprint and inverted load capacity factor for OECD countries. J. Environ. Manag. 365, 121551. https://doi.org/10.1016/j.jenvman.2024.121551.

Deng, W., Kharuddin, S., Mohd Ashhari, Z., 2024. Green finance transforms developed countries' green growth: mediating effect of clean technology innovation and threshold effect of environmental tax. J. Clean. Prod. 448, 141642. https://doi.org/10.1016/j.jclepro.2024.141642.

Dietz, T., Rosa, E.A., 1997. Effects of population and affluence on CO₂ emissions. Proc. Natl. Acad. Sci. 94, 175–179. https://doi.org/10.1073/pnas.94.1.175.

Doumon, N.Y., 2024. Transitioning to renewable energy: Challenges and opportunities. In: Transitioning to Renewable Energy: Challenges and Opportunities. https://iee.psu.edu/news/blog/transitioning-renewable-energy-challenges-and-opportunities.

EU, 2020. Technical Support for Implementing the European Green Deal, 2020. https://doi.org/10.2887/605908.

Grossman, G.M., Krueger, A.B., 1995. Economic growth and the environment. Q. J. Econ. 110, 353–377. https://doi.org/10.2307/2118443.

Gu, X., Baig, I.A., Shoaib, M., Zhang, S., 2024. Examining the natural resources-ecological degradation nexus: the role of energy innovation and human capital in BRICST nations. Res. Policy 90, 104782. https://doi.org/10.1016/j.resourpol.2024.104782.

Hakkak, M., Altintaş, N., Hakkak, S., 2023. Exploring the relationship between nuclear and renewable energy usage, ecological footprint, and load capacity factor: a study of the Russian Federation testing the EKC and LCC hypothesis. Renew. Energy Focus 46, 356–366. https://doi.org/10.1016/j.ref.2023.07.005.

Han, Y., Sun, L., 2024. Frontier technology readiness and mineral resources utilization effect on load capacity factor: mediating function of fintech indicators. Res. Policy 98, 105334. https://doi.org/10.1016/j.resourpol.2024.105334.

Herwartz, H., Maxand, S., Raters, F.H.C., Walle, Y.M., 2018. Panel unit-root tests for heteroskedastic panels. Stata J. 18, 184–196. https://doi.org/10.1080/07474938.2014.966638.

Javed, A., Rapposelli, A., Khan, F., Javed, A., Abid, N., 2024. Do green technology innovation, environmental policy, and the transition to renewable energy matter in times of ecological crises? A step towards ecological sustainability. Technol. Forecast. Soc. Chang. 207, 123638. https://doi.org/10.1016/j.techfore.2024.123638.

Khan, S., Akbar, A.J., Nasim, I., Hedvicaková, M., Bashir, F., 2022. Green finance development and environmental sustainability: a panel data analysis. Front. Environ. 10. https://doi.org/10.3389/fenvs.2022.1039705.

Kish, K., Miller, E., 2025. Broadening ecological footprint and biocapacity research: a co-developed research agenda with Canadian stakeholders. Ecol. Econ. 227, 108403. https://doi.org/10.1016/j.ecolecon.2024.108403.

Koengkan, M., Fuinhas, J.A., Tavares, A.I.P., Gonçalves Silva, N.M.B., 2023. 7 - Causes of environmental degradation in the Latin American and Caribbean region. In: Koengkan, M., Fuinhas, J.A., Tavares, A.I.P., Gonçalves Silva, N.M.B. (Eds.), Obesity Epidemic and the Environment. Academic Press, pp. 173–217. https://doi.org/10.1016/B978-0-323-99339-5.00002-9.

Li, S., Hu, K., Kang, X., 2024. Impact of financial technologies, digitalization, and natural resources on environmental degradation in G-20 countries: Does human resources matter? Res. Policy 93, 105041. https://doi.org/10.1016/j.resourpol.2024.105041.

Ma, F., Saleem, H., Ding, X., Nazir, S., Tariq, S., 2024. Do natural resource rents, green technological innovation, and renewable energy matter for ecological sustainability? Role of green policies in testing the environmental kuznets curve hypothesis. Res. Policy 91, 104844. https://doi.org/10.1016/j.resourpol.2024.104844.

Machado, J., Silva, S., 2019. Quantiles via moments. J. Econ. 213, 145–173. https://doi.org/10.1016/j.jeconom.2019.04.009.

Mance, D., Vilke, S., Debelić, B., 2020. Sustainable governance of coastal areas and tourism impact on waste production: panel analysis of Croatian municipalities. Sustainability 12, 7243. https://doi.org/10.3390/su12187243.

Matei, D., Christoph, H., 2010. Unit Root Testing in Heteroskedastic Panels Using the Cauchy Estimator. https://hdl.handle.net/10419/37368.

Mehmood, U., Tariq, S., Aslam, M.U., Agyekum, E.B., Uhunamure, S.E., Shale, K., Kamal, M., Khan, M.F., 2023. Evaluating the impact of digitalization, renewable energy use, and technological innovation on load capacity factor in G8 nations. Sci. Rep. 13, 9131. https://doi.org/10.1038/s41598-023-36373-0.

Montenegro, R.L.G., Ribeiro, L.C., Gustavo, G., 2021. The effects of environmental technologies: evidences of different national innovation systems. J. Clean. Prod. 284, 124742. https://doi.org/10.1016/j.jclepro.2020.124742.

Musah, M., Ahakwa, I., Asongu, S.A., Owusu-Akomeah, M., Ampong, G.O.A., 2024. Unlocking the COP28 climate agenda in G10 economies: do environmental taxes and environmentally-related technologies matter in the natural resource-load capacity factor connection? Sustain. Futures 8, 100341. https://doi.org/10.1016/j.sftr.2024.100341.

Nguyen, D.K., Huynh, T.L.D., Nasir, M.A., 2021. Carbon emissions determinants and forecasting: evidence from G-6 countries. J. Environ. Manag. 285, 111988. https://doi.org/10.1016/j.jenvman.2021.111988.

Pal, S., Villanthenkodath, M.A., Ansari, M.A., 2025. A comparative study on the moderating impact of renewable energy and innovation on environmental quality. Nat. Res. Forum. https://doi.org/10.1111/1477-8947.12420.

Qin, D., Ding, Y., Zhai, P., Song, L., Luo, Y., Jiang, K., 2023. Adaptation and mitigation: measures, actions and effects. In: Qin, D., Ding, Y., Zhai, P., Song, L., Luo, Y., Jiang, K. (Eds.), The Change of Climate and Ecological Environment in China 2021: Synthesis Report. Springer Nature Singapore, Singapore, pp. 129–164.

Quan, Z., Xu, X., Jiang, J., Wang, W., Gao, S., 2024. Uncovering the drivers of ecological footprints: a STIRPAT analysis of urbanization, economic growth, and energy sustainability in OECD countries. J. Clean. Prod. 475, 143686. https://doi.org/10.1016/j.jclepro.2024.143686.

Sakariyahu, R., Fagbemi, T., Adigun, R., Lawal, R., Seyingbo, O., Oyekola, O., 2024. Severity of environmental degradation and the impact on quality of life in Africa. J. Environ. Manag. 356, 120537. https://doi.org/10.1016/j.jenvman.2024.120537.

Sarkodie, S.A., 2021. Environmental performance, biocapacity, carbon & ecological footprint of nations: drivers, trends and mitigation options. Sci. Total Environ. 751, 141912. https://doi.org/10.1016/j.scitotenv.2020.141912.

Sarwar, N., Bibi, F.U.N., Junaid, A., Alvi, S., 2024. Impact of urbanization and human development on ecological footprints in OECD and non-OECD countries. Heliyon 10, e38058. https://doi.org/10.1016/j.heliyon.2024.e38058.

Schneider, N., 2022. Unveiling the anthropogenic dynamics of environmental change with the stochastic IRPAT model: a review of baselines and extensions. Environ. Impact Assess. Rev. 96, 106854. https://doi.org/10.1016/j.eiar.2022.106854.

Sharif, A., Bashir, U., Mehmood, S., Cheong, C.W.H., Bashir, M.F., 2024. Exploring the impact of green technology, renewable energy and globalization towards environmental sustainability in the top ecological impacted countries. Geosci. Front. 15, 101895. https://doi.org/10.1016/j.gsf.2024.101895.

Shayanmehr, S., Riza, R., Baba, A.E., Kwame, O.E., Sunday, A.T., Gyamfi, B.A., 2023. How do environmental tax and renewable energy contribute to ecological sustainability? New evidence from top renewable energy countries. Int. J. Sustain. Dev. World Ecol. 30, 650–700. https://doi.org/10.1080/13504509.2023.2186961.

Shazhad, Q., Aruga, K., 2024. Spatial effect of economic performance on the ecological footprint: evidence from Asian countries. Environ. Dev. Sustain. https://doi.org/10.1007/s10668-024-05134-y.

Soergel, B., Kriegler, E., Weindl, I., Rauner, S., Dirnaichner, A., Ruhe, C., Hofmann, M., Bauer, N., Bertram, C., Bodirsky, B.L., Leimbach, M., Leininger, J., Levesque, A., Luderer, G., Pehl, M., Wingens, C., Baumstark, L., Beier, F., Dietrich, J.P., Humpenöder, F., von Jeetze, P., Klein, D., Koch, J., Pietzcker, R., Strefler, J., Lotze-Campen, H., Popp, A., 2021. A sustainable development pathway for climate action within the UN 2030 agenda. Nat. Clim. Chang. 11, 656–664. https://doi.org/10.1038/s41558-021-01098-3.

Sohag, K., Husain, S., Soytas, U., 2024. Environmental policy stringency and ecological footprint linkage: mitigation measures of renewable energy and innovation. Energy Econ. 136, 107721. https://doi.org/10.1016/j.eneco.2024.107721.

Sun, X., Rasool, Z., 2024. Unlocking the green vault: a comparative analysis on the impact of green financing initiatives in mitigating ecological footprint in Europe. Borsa Istanbul Rev. 24, 95–105. https://doi.org/10.1016/j.bir.2023.10.014.

Sun, C., Khan, A., Cai, W., 2024a. The response of energy aid and natural resources consumption in load capacity factor of the Asia Pacific emerging countries. Energy Policy 190, 114150. https://doi.org/10.1016/j.enpol.2024.114150.

Sun, Y., Usman, M., Radulescu, M., Korkut Pata, U., Balsalobre-Lorente, D., 2024b. New insights from the STIPART model on how environmental-related technologies, natural resources and the use of the renewable energy influence load capacity factor. Gondwana Res. 129, 398–411. https://doi.org/10.1016/j.gr.2023.05.018.

Touati, K., Ben-Salha, O., 2024. Reconsidering the long-term impacts of digitalization, industrialization, and financial development on environmental sustainability in GCC countries. Sustainability 16, 3576.

Uche, E., Ngepah, N., Das, N., Dey, L., 2024. Dynamic interactions of green innovations, green transitions and ecological load capacity factor in BRICS. Renew. Energy 231, 120905. https://doi.org/10.1016/j.renene.2024.120905.

Ul-Durar, S., Arshed, N., De Sisto, M., Nazarian, A., Sadaf, A., 2024. Modeling green energy and innovation for ecological risk management using second generation dynamic quantile panel data model. J. Environ. Manag. 366, 121741. https://doi.org/10.1016/j.jenvman.2024.121741.

Villanthenkodath, M.A., Pal, S., 2024. Environmental degradation in geopolitical risk and uncertainty contexts for India: a comparison of ecological footprint, CO2 emissions, and load capacity factor. Energy Clim. Change 5, 100122. https://doi.org/10.1016/j.egycc.2023.100122.

Villanthenkodath, M.A., Ansari, M.A., Balsalobre-Lorente, D., Satrovic, E., 2024a. The comprehensive impact of economic growth on environmental quality: insight established on material, carbon, and ecological footprint. Operat. Res. For. 5, 70. https://doi.org/10.1007/s43069-024-00355-3.

Villanthenkodath, M.A., Pal, S., Ansari, M.A., 2024b. Unlocking sustainable development, 2024b: evaluating the impact of monetary and fiscal policies on ecological footprint in India. World Developm. Sustain. 5, 100186. https://doi.org/10.1016/j.wds.2024.100186.

Wang, F., Taghvaee, V.M., 2023. Impact of technology and economic complexity on environmental pollution and economic growth in developing and developed countries: using IPAT and STIRPAT models. Environ. Sci. Pollut. Res. 30, 73349–73360. https://doi.org/10.1007/s11356-023-27569-y.

Wang, C., Zheng, C., Chen, B., Wang, L., 2024. Mineral wealth to green growth: navigating FinTech and green finance to reduce ecological footprints in mineral rich developing economies. Res. Policy 94, 105116. https://doi.org/10.1016/j.resourpol.2024.105116.

Xing, L., Khan, Y.A., Arshed, N., Iqbal, M., 2023. Investigating the impact of economic growth on environment degradation in developing economies through STIRPAT model approach. Renew. Sust. Energ. Rev. 182, 113365. https://doi.org/10.1016/j.rser.2023.113365.

Zhang, S., Chen, K., 2023. Green finance and ecological footprints: natural resources perspective of China's growing economy. Res. Policy 85, 103898. https://doi.org/10.1016/j.resourpol.2023.103898.

Zhang, Y., Radmehr, R., Baba Ali, E., Samour, A., 2024. Natural resources, financial globalization, renewable energy, and environmental quality: novel findings from top natural resource abundant countries. Gondwana Res. https://doi.org/10.1016/j.gr.2023.12.016.