

# Does agriculture, forests, and energy consumption foster the carbon emissions and ecological footprint? fresh evidence from BRICS economies

Iftikhar Yasin<sup>1</sup> · Nawaz Ahmad<sup>1</sup> · Saqib Amin<sup>2</sup> · Nyla Sattar<sup>1</sup> · Afsheen Hashmat<sup>1</sup>

Received: 25 July 2022 / Accepted: 29 December 2023 © The Author(s), under exclusive licence to Springer Nature B.V. 2024

#### Abstract

Protecting the environment is essential because a healthy ecosystem purifies air and water, maintains the soil, regulates the temperature, recycles nutrients, and provides food. However, when nations experience fast growth, they pay the utmost attention to their development and disregard the environmental and development-related consequences. The BRICS economies are examples of nations that have achieved high economic growth rates while polluting their environment via industrial expansion. Hence, this study aims to scrutinise the effects of forest rent, agricultural production, economic growth, and energy consumption on BRICS economies' carbon emissions and ecological footprint from 1995 to 2017. We adopted panel spatial correlation consistent least-squares dummy variables (PSCC-LSDV) estimation and panel quantile regression (PQR) techniques to perform the abovementioned comparative analysis. The first-hand empirical consequences revealed that agricultural production, renewable energy consumption, and financial development condense the carbon discharge, and the rest of the variables trigger the carbon emission. In addition, GDPC, forest rents, non-renewable energy consumption, and domestic investment damage the environmental prominence by instigating an ecological footprint, whereas the remaining variables oblige to moderate the ecological footprint. Finally, this study recommends rigorous policies to mitigate pollution emissions to help reinstate environmental eminence.

Keywords Ecological footprint  $\cdot$  CO $_2$  emission  $\cdot$  Forests  $\cdot$  Agriculture  $\cdot$  Energy consumption

# 1 Introduction

Economic growth throughout the globe has surged to unprecedented levels in the last several decades. Additionally, developing economies account for a large portion of this expansion (Ahmed, 2017; Yasin et al., 2021). Further, technological development has been genuinely escalating, and that has assisted in improving life. However, it has generated several environmental challenges, for instance, perfluorocarbon releases (Waheed et al., 2018; Yasin et al., 2023). Notably, the emerging states in Brazil, Russian Federation, India, China, and South Africa (BRICS) countries have become progressively

Extended author information available on the last page of the article

affluent in recent decades (Azevedo et al., 2018). The emerging national economies of BRICS have also triggered several environmental issues, especially carbon dioxide (CO<sub>2</sub>) emissions (Dong et al., 2017). The primary source of greenhouse gas emissions (GHG) or CO<sub>2</sub> releases is the usage of fossil fuels in almost every sector. For instance, transportation of agriculture production, electricity generation, and about 25 percent of greenhouse gas discharges are because of the production of heat and electricity. Forest, agriculture, and other usages of land are the second major emitter of greenhouse gas releases. As a result, it accounts for 24% of all greenhouse gas emissions worldwide (Waheed et al., 2018).

The destruction of the environment expands beyond greenhouse gas (GHG) emissions or CO<sub>2</sub> releases alone. It helps to consider the adverse effects of the environment of all kinds of actions from humans on the biosphere as capsulated in the frame of ecological footprint. The ecological footprint is a scientific accounting indicator. It discourses the concern at what amount of natural endowments should be used within the framework of the regenerating capacity of the earth. Furthermore, ecological footprint it measures the ecological assets a population or product requires to produce the natural resources it consumes, including food obtained from plants and products of fiber, fish and livestock products, other forest products and timber, and land required for urban infrastructure, and to dissipate its wastages, particularly emissions of carbon. It has been measured based on the amount of biologically productive area that can support the consumption of resources in a unit named global hectares. The world can be saved from a global climate disaster by cutting carbon emission levels. This is not the agenda for an immediate pollution-free environment or zero net emission, but at least when considering the huge damage caused by humans' actions on the biosphere. The ice-free land is about 25% of the globe prone to degeneration. 70% of the earth's surface free of ice is directly harmed by the actions of humans (Alola et al., 2022). The ecological footprint is a superior metric for gauging the extent of environmental damage over emissions of greenhouse gases (Yasin et al., 2020). Rees (1992) and Wackernagel and Rees (1998) developed this and further elongated by Rees and Wackernagel (2008). It encompasses natural productive land and water areas, so individuals use them for production and consumption (Charfeddine, 2017). The production of agriculture and domestic products are also the primary source of instigating human demand on nature.

The fuel-wood supplied 7 per cent of energy consumption globally, but now the use of fuel wood might be declining slowly due to increased charcoal production. The fuel wood comes from natural forests, shrublands, plantations, woodlands, and trees from outside the forests, especially in developing countries. The fuel wood is mostly from the processing of industrial round wood, and almost 50 per cent or more logs are utilised for energy in developed economies (Mead, 2005). The trees are carbon absorber that supports condensing carbon dioxide from the atmosphere. Though, the contribution of forests may also raise carbon dioxide release in various ways (Waheed et al., 2018). In the first place, forest fires release a significant amount of CO<sub>2</sub>. Among other examples, forest fires grew in smoke by 119,000 acres in the United States in 2016 (Ahillen, 2016). Secondly, as a result of photosynthesis, it is transformed into an organic substance. As the plants breathe, they release carbon dioxide into the atmosphere. In order to know whether forestry is a carbon source or sink, we must look at how stable these orders are. Third, following a massive tree die-off, it is expected that soil bacteria would release stored carbon dioxide into the atmosphere. Lastly, one of the chief reasons for CO<sub>2</sub> secretion worldwide is deforestation, which is about 17% (Baccini et al., 2012). The annual carbon dioxide emissions caused by deforestation amount to around 5800 million tonnes (Menon et al., 2007). Moreover, one of the economical ways to condense  $CO_2$  release is by controlling or stopping the activities of deforestation (Stern, 2008).

Furthermore, environmental factors also affect the agriculture sector. Rain and temperature play a prominent role in agriculture. When climate changes occur, the cycle of rain, magnitude, and the timing of rain change, leaving the farmers unaware of this to alter. Conversely, the water is held in the form of moisture when the temperature is warm. The soil's moisture quickly changes into evaporation and leaves less water for crop production in arid areas (Kang et al., 2009; Magadza, 2000). According to the US emanation inventory, the agricultural sector accounts for a minimum of 8% of greenhouse gas emissions in the United States. Methane and nitrous oxide from soil management and livestock husbandry are the chief sources of these releases (Holly et al., 2017; Waheed et al., 2018).

Each country in the BRICS economies is continuously improving with economic development. The BRICS nations are some of the most populous and highly regarded new powers on the global stage. Their enormous population and promising economic outlook put them ahead of many other developing countries. By 2021, BRICS will account for 41 per cent of the world's population, 16 per cent of global commerce, and 24 per cent of the world's GDP, all growing at a pace of 6.24 per cent. In 1990, the United States, Japan, OECD nations, Brazil, India, China, and the Russian Federation accounted for 23%, 5.72%, 24%, 0.94%, 3%, 11%, and 3.8% of all energy-related carbon emissions, respectively. In 2007, Japan's and the United States' emissions decreased by 5% and 22%, respectively, while those of the BRICS nations rose, and these countries are still causing environmental degradation. Hence, the vigorous development in these five countries has made environmental issues more vital (Hashmi et al., 2023; Liu et al., 2022).

The BRICS nations are among the highest carbon dioxide emitters in the world, according to data from the World Bank. China was responsible for 28 per cent of global emissions in 2019, followed by the United States with 15 per cent and India with 7 per cent. Russia and Brazil were among the top ten emitters, with 4 and 2 per cent, respectively. Moreover, the environmental footprint of these nations is substantial. According to the Global Footprint Network, in 2019, China had a per capita ecological footprint of 2.6 global hectares, India had a footprint of 1.7 global hectares, Brazil had a footprint of 2.5 global hectares, Russia had a footprint of 5.2 global hectares, and South Africa had a footprint of 5.3 global hectares. These numbers indicate that the ecological footprint per capita in the BRICS nations is significantly larger than the global average.

Hence, this research aims to assess the influence of forests, agricultural output, energy consumption, and economic development on  $CO_2$  emissions and ecological footprints in BRICS countries. Figures 1 and 2 indicate that carbon emissions and ecological footprints substantially increase in the BRICS nations despite increased environmental quality concerns. This research examines the impacts of renewable and non-renewable energy consumption, forest rents, agricultural output, financial development, domestic investment, and economic growth on  $CO_2$  emissions for the BRICS nations. Due to the paucity of research on the effects of non-renewable energy consumption, forest rents, financial development, agricultural output, domestic investment, and economic growth on the ecological footprints of the BRICS nations, we also investigated these factors in this study. This study has a manifold contribution to the existing literature. To our knowledge, this is the first study to examine the environmental bearing of agricultural products and forests for BRICS economies in the case of both carbon emissions and ecological footprints. Secondly, this study will also examine the environmental impact of forest rent and perform a comparative analysis of both carbon emissions and ecological footprints. Lastly, this study will perform the comparative analysis of carbon emissions and ecological footprints by incorporating panel



Fig. 1 Carbon emissions of BRICS. Vertical axis measures carbon emissions



Fig. 2 Ecological footprints of BRICS. Vertical axis measures carbon emissions

quantile regression (PQR) and panel spatial correlation consistent least-squares dummy variables (PSCC-LSDV). Therefore, this recent study intends to fill the gap by examining the environmental eminence of BRICS economies by performing a comparative analysis of carbon emissions and ecological footprints.

### 2 Literature review

The ecological footprint and threatened highlands of the Atlantic Forest were investigated by Bogoni et al. (2018). The study's results showed the understanding of animal and plant relationships under the highlands of the Atlantic, where regions or habitats are different in management. Therefore, the study concludes that human actions directly change the distribution pattern. However, on the other hand, species diversity exists in the direction of interspecific interactions. Hashmi et al. (2023) explored the environmental impact of financial globalisation and governance quality in BRICS-T economies from 2000 to 2020. They incorporated CS-ARDL and discovered that while de jure financial globalisation is restoring environmental quality, de facto financial globalisation is deteriorating. They observed that renewable energy could help to reduce carbon emissions, which are caused by urbanisation.

Irfan et al. (2022) investigated the effect of air contaminants containing nitrous oxide, carbon emissions, and nitrogen oxides on ecological footprint, cropland, and forestry area by taking other control variables. They covered the time from 1975 to 2020. They employed Johansen cointegration and error correction model and elasticities. The study revealed that carbon emission, nitrous oxide, and trade openness decrease the pressure on the ecological footprint in the long run. In contrast, nitrogen oxide and GDP hurt the ecological footprints by using more natural resources to produce goods and services. Conversely, carbon emission concentration rises as forestry area increases while nitrogen oxide hurts the cropland. The error correction mechanism revealed that the speed of adjustment is 90% for forestry areas, 50% for ecological footprints, and 40% for cropland.

Ansari (2022) examined the environmental Kuznets curve (EKC) by comparing ecological footprint and carbon emission for ASEAN countries, covering the time from 1991 to 2016. They used the second generation panel unit root tests, covariate augmented Dickey–Fuller (CADF) and cross-sectional Im, Pesaran, and Shin (CIPS) tests, Westerlund cointegration test, fully modified ordinary least square (FMOLS) and pooled mean group (PMG). The result shows that the "inverted U-shaped hypothesis" is valid in ASEAN using the ecological footprints, while EKC is not in these countries using carbon emissions. Nonrenewable energy affects ecological footprints and carbon emissions positively and significantly, while renewable energy consumption reduces environmental contamination in these countries. A one-way causality exists between economic growth and degradation of the environment, whereas a two-way causality lies among non-renewable energy consumption and ecological footprints.

Tuna (2022) explored biomass energy consumption's influence on the environment's degradation for BRICS economies using data from 1992 to 2018. They used Pedroni and Kao cointegration and FMOLS and DOLS tests to estimate long-run coefficients. They found that biomass energy consumption causes to reduce carbon emission but raises ecological footprints. Moreover, economic growth increases carbon emissions and ecological footprints, while urbanisation helps cut emissions.

Mehmood (2022) probed the relationship among financial development, renewable and non-renewable energy consumption, agricultural value added, forest area, and ecological footprints for South Asian countries from 1990 to 2018. They used cross-sectional dependence (CD) and cross-sectional autoregressive distributed lag (CS-ARDL). A strong cointegration relationship exists among the panel data. The empirical findings show that forest area, renewable energy, and financial development are helpful in Sri Lanka, India, Bangladesh, and Pakistan.

Furthermore, Alola et al. (2022) studied China's ecological footprint dynamics. They covered the period from 1971 to 2016. They employed quantile-on-quantile regression (QQR), quantile regression, and spectral Granger causality (SGC) for analysis. The outcomes of quantile-on-quantile regression revealed that economic growth positively impacts ecological footprint, particularly in medium quantiles and each quantile of economic growth. Further, fossil fuel and primary energy usage positively affect each quantile of the ecological footprint and the two energy profiles.

Moreover, renewable energy usage positively affects the ecological footprint at the lower tail and renewable energy usage at the higher tail. In addition, the result of spectral Granger causality found that one-way causality runs from primary energy usage and economic growth to the ecological footprint in the long run. Additionally, without reverse, there is unidirectional causality from renewable energy usage to the ecological footprint in the short, medium, and long run.

Wenlong et al. (2022) applied QARDL to examine the effect of economic globalisation, coal rents, electricity consumption, and transportation on the ecological footprint of the US from 1995 to 2018. The findings show that transportation, coal rents, and globalisation positively and significantly reduce the ecological footprints at different quantile ranges in the short and long term. Electricity consumption positively and significantly affects the ecological footprint at the lower quantile level in the long run but does not have a significant effect in the short run.

For BRICS countries, Pata (2021) analysed the influence of renewable energy, agricultural activities, and globalisation on  $CO_2$  emissions and ecological footprint. This study is from 1971 to 2016, and Fourier cointegration and causality tests have been used. The longrun cointegration exists among variables for China and Brazil, and the long-term elasticities show that globalisation increases environmental pollution, but renewable energy significantly decreases the environmental burden in China. Furthermore, globalisation increases  $CO_2$  emissions, while renewable energy improves environmental quality in Brazil. The findings of the causality test show that the two-way causality lies between agriculture and the degradation of the environment.

Conversely, one-way causality runs from globalisation to  $CO_2$  emissions and ecological footprint and renewable energy generation towards ecological indicators. Overall, renewable energy can significantly decrease environmental degradation in China and Brazil. Conversely, renewable energy does not influence the environmental burden in India and Russia.

Khan et al. (2021) investigated the influence of population increase, natural resources, and energy use on US environmental deterioration. They covered the time from 1971 to 2016. They employed breakpoint ADF unit root test, structural break Zivot-Andrew unit root test, and GMM. The outcomes revealed that cointegration exists between the variables. Long-term improvements in environmental quality may be achieved by increasing the use of renewable energy and natural resources.

In contrast, population growth and non-renewable energy consumption make the environment worse. The two-way causation exists among carbon emissions, natural resources, and ecological footprints. In comparison, one-way causation exists between population growth, carbon releases, ecological footprint, and energy consumption.

Alvarado et al. (2021) assessed the impact of research and development on the degradation of the environment in terms of ecological footprint and quality of air, together with the role of trade and agriculture by using environmental Kuznets curve. The secondgeneration cointegration techniques have been used for 77 countries covering the period of 1996 to 2016. The cointegration association has been found among research and development, environmental contamination, trade, and agriculture. Moreover, research and development have a heterogeneous impact on environmental contamination. Similarly, two-way causality has been found between research and development, air quality, and the ecological footprint and research and development. The bidirectional causal relation exists between air quality and research and development in East Asia and the Pacific region. The bidirectional causality runs from the ecological footprint to research and development in North Africa and the Middle East. Lastly, the unidirectional causality exists between research and development and ecological footprint in Central Asia, North America, and Europe. Yasin et al. (2020) analysed the effects of energy consumption, urbanisation, political institutions, financial development, and trade openness on ecological footprints (EF). From 1996 to 2016, they took 110 less developing and developed economies and employed panel EGLS and multi-step A-B GMM. They discovered that EKC occurs in these economies and that trade openness, urbanisation, and political institutions have positive environmental effects. In contrast, energy consumption and composition impacts have negative environmental repercussions.

Besides, in China, Ahmed et al. (2020) looked at the impact of human capital, urbanisation, and abundant natural resources on the country's ecological footprint. They took data for 1970–2016 and employed the bootstrap causality method and Bayer and Hack cointegration test. The outcomes confirmed the longer-term equilibrium association among variables. Further, the rent of natural resources raises the ecological footprint. Economic development and urbanisation exacerbate environmental deterioration, but human capital has the opposite effect. They found that the interaction term between human capital and urbanisation assists in relieving environmental destruction. It specifies a dampening impact of human capital that encourages sustained urbanisation. The estimations of the bootstrap causation technique disclosed one-way causation from natural resources to the ecological impacts.

Nathaniel and Khan (2020) explored the effect of energy consumption, ecological footprint, urbanisation, and economic growth in ASEAN economies by covering the period from 1990 to 2016. They exposed that non-renewable energy, economic growth, and trade contributed to environmental damage. They also found that unidirectional causation flows urbanisation towards non-renewable energy consumption.

Ecological footprint, consumption of energy, and urbanisation in North Africa and Middle East countries are scrutinised by Nathaniel et al. (2020). They used data for 1190–2016. They employed an augmented mean group algorithm. They showed that pollution is caused by urbanisation, the use of non-renewable energy, financial development, and economic growth. Nguyen et al. (2020) examined the foremost drivers of agricultural releases by considering the affluence, value-added of agriculture, the intensity of energy, and economic amalgamation. They used panel data for 89 states and the time covered from 1995 to 2012. They applied the dynamic fixed effects autoregressive distributed lag technique.

Azam (2019) investigated the impact of environmental degradation, energy, human and physical capital, and financial development on economic growth in four BRICS countries except for Russia. Environmental pollution inhibits economic growth, but energy consumption, human capital, physical capital, and financial development contribute to economic growth, as RLS and FMOLS show. Zhang and Wang (2019) inspected carbon release and investment in research and development in BRICS states from 1996 to 2014. They employed fully modified ordinary least squares. The outcomes showed that a rise in research and development investment caused a reduction in the carbon releases in BRICS, but this influence is weak in India and Russia. The researchers discovered that urbanisation and industrialisation hinder the decoupling between carbon emissions and economic development, but renewable energy has assisted it.

For the BRICS countries, Azevedo et al. (2018) looked at carbon dioxide emissions  $(CO_2)$  based on a lag between releases and GDP from 1980 to 2011. In order to account for the wide range of CO<sub>2</sub> emissions among the BRICS countries, they divided the countries into two distinct categories. Group 1 concluded that the major causes of the discrepancy in CO<sub>2</sub> emissions are the country's yearly GDP and lagged CO<sub>2</sub> emissions (Russia & Brazil). According to Group 2, the outcomes were unaffected by differences in GDP; instead, they

were solely determined by emissions of  $\text{CO}_2$  during the lag period (India, South Africa & China).

Waheed et al. (2018) looked into Pakistan's carbon dioxide (CO<sub>2</sub>) emissions and the use of renewable energy, agriculture, and the country's forests. They employed the autoregressive distributed lag model and found that renewable energy and forestry consumption negatively and substantially influence CO<sub>2</sub> release in the long run. In addition, renewable energy and forest areas might minimise CO<sub>2</sub> emissions. They inferred that agriculture is a significant carbon source in Pakistan. They determined that planting forests cut CO<sub>2</sub> emissions more than agribusiness and renewable energy.

Further, Zaman et al. (2017) inspected the causative connection between natural resources, contamination of the environment, climatic variation, and energy consumption in Pakistan. They covered the period from 1975 to 2012. They employed the Granger causality and bivariate cointegration method. The outcomes revealed that the demand for energy raises the rents of natural resources, oil, and gas, whereas it depletes the natural resources. The two-way causation runs from the energy demand to the rent of oil, net forest exhaustion to climatic fluctuations, natural resource exhaustion to environmental damage, and forest rents to carbon secretions. One-dimensional causation exists amongst net forest exhaustion and carbon discharges, carbon releases and oil rents, climatic fluctuations and rents of the forest, oil, natural gas, and minerals. Lastly, the "neutrality hypothesis" has been affirmed among rents of natural gas, coal, and climatic variations in Pakistan.

Ahmed (2017) explored the connection between growth and energy in the case of newly industrialising by incorporating major financial indicators for BRICS states. They found that energy efficiency improves if income rises over a certain point due to financial development and capital accumulation. Dong et al. (2017) evaluated the relationship between renewable energy use, carbon emissions, GDP, and natural gas using the environmental Kuznets curve. They took data from 1985 to 2016 for BRICS. According to their AMG calculation, increasing renewable energy and natural gas use reduces carbon emissions. In the long run, renewable energy and natural gas usage are linked.

Gauli and Upadhyay (2013) have reviewed REDD in Nepal. The Nepali government is determined with REDD to turn deforestation and degradation of forests, safeguarding existing forests and improving forest carbon stocks. Since 2009, the state's economy and way of life have grown hand in hand with adopting a long-term vision for the forest's source. Nepal has considered a specific stratagem for later because it would suffer in various arenas throughout the process. Nepal is a minor developing economy, so it can benefit from REDD following the provided information by over-viewing its holistic prospect, potency, and aspects.

Atmadja et al. (2012) reviewed research on policies and strategies to escape from mitigating forest degradation and deforestation emanations. Most studies published before 2005 evaluated emissions based on fossil fuel leaks from large-scale interventions such as the United Nations Framework Convention on Climate Change Kyoto Protocol. Some studies concern land-use emissions, which are more suitable for reducing emissions from deforestation and forest degradation (REDD) and arose later, while others have concentrated on small-scale interventions. So, the qualitative studies have deficiencies in expressing the development of leakage from interventions and how factors are influenced in this process. Therefore, empirical studies have needed to grasp activities deeply, the source of emanations, how the policies influence the actions of carbon discharge, and consequently, how much emission is produced.

Dale et al. (2001) discussed climate change and forests in this context. Climatic fluctuation affected the forests by changing the fire's duration, frequency, intensity, and timing, introducing species, heat waves, outbursts of insects and pathogens, silver storms, windstorms, tornadoes, and landslides. The fluctuations in disruption regimes are a natural part of all ecosystems over geological time. The amount and intricacy of climatic variables associated with forest disruption made integrating research a significant challenge. Hence, it is crucial to consider different ways to overcome the influence of climatic varition, which disrupts the forest system, because fluctuation cannot always be prognosticated.

Thus, the primary literature indicates that almost no research has examined the influence of forest rent, domestic investment, agricultural products, financial development, and renewable and non-renewable energy use on BRICS states' carbon emissions and ecological footprints. Hence, comparing carbon emissions and ecological footprints amongst BRICS countries is needed to fill the gap.

#### 3 Theoretical framework and model specification

The influence of human actions on the environment has been analysed by an extensively recognised formula: IPAT identity (Harrison & Pearce, 2000; Stern et al., 1992). The IPAT identity was developed by Ehrlich and Holdren (1971). It is based on the primary drivers of anthropogenic environmental impressions in the early 1970s and is extensively used to analyse the significant forces of environmental transformation (Raskin, 1995; Yasin et al., 2021; York et al., 2002). The IPAT equation specifies the influence of population (*P*), affluence (*A*), and technology (*T*) on environmental impacts; henceforth, I=PAT (Raskin, 1995; Yasin et al., 2021; York et al., 2003). The greatest strength of the IPAT model is that it defines the main drivers behind the transformation of the environment with parsimony. In addition, it expresses the mathematical relationship between significant forces and their effects mathematically (Dietz & Rosa, 1997).

Waggoner and Ausubel (2002) proposed the ImPACT method based on the IPAT model. To put it another way, the ImPACT model predicts total  $CO_2$  emissions as a product of the following factors: population (*P*), GDP per capita (*A*), per capita consumption of energy (*C*), and  $CO_2$  per unit of energy used (*T*). Further, Schulze (2002) has implied another elongation of IPAT with the addition of the factor behaviour in this model, and it is *I*=PBAT; however, each of the variables on the right side of the equation *I*=PAT already accounts for this behaviour (Diesendorf, 2002; Roca, 2002). Although IPAT and ImPACT are flexible, scaled, and easy to identify the effect of driving forces on the environment, they nevertheless have significant constraints. IPAT and ImPACT both have assumed proportionality among the prime determinant factors. So, one factor is constant when another factor is changed.

Non-proportional or non-monotonic effects of driving elements are also not included in these models (York et al., 2003). So, Dietz and Rosa (1997) introduced a new model to handle these limits, called the STIRPAT model. This model is fused to test the propositions empirically because it no longer has an accounting equation. Hence, this model is presented below;

$$I_{\rm it} = \varphi P_{\rm it}^x A_{\rm it}^y T_{\rm it}^z \in_{\rm it}$$
(1)

In Eq. (1),  $\varphi$  denotes the constant, and *x*, *y*, and *z* are the exponents of the population (*P*), affluence (*A*), and technology (*T*). The subscript '*i*' denotes the cross sections and time sequentially.  $\in$  denotes the error term. Now that the logarithm is taken on both sides, we obtain;

$$\ln I_{it} = \ln \varphi + x \ln P_{it} + y \ln A_{it} + z \ln T_{it} + \ln \epsilon_{it}$$
<sup>(2)</sup>

We extended the model given in Eq. (2) by following Waheed et al., (2018) and incorporated non-renewable energy consumption, domestic investment, and economic growth for the case of BRICS economies. Hence, the model has been extended as follows:

$$\ln \text{ENvD}_{it} = \ln \varphi_0 + \varphi_1 \ln \text{REC}_{it} + \varphi_2 \ln \text{non} \text{REC}_{it} + \varphi_3 \ln \text{FR}_{it} + \varphi_4 \ln \text{GDPC}_{it} + \varphi_5 \ln \text{DI}_{it} + \varphi_6 \ln \text{AP}_{it} + \varphi_7 \ln \text{FD}_{it} + \epsilon_{it}$$
(3)

In the above equation, EnvD represents the environmental damage.

#### 4 Methodology and data source

We have chosen two techniques for this study: panel quantile regression (PQR) and panel spatial correlation consistent least-squares dummy variables (PSCC-LSDV). We applied the panel quantile regression (PQR) method because many studies have chosen the conventional OLS procedure to analyse the influencing elements for CO<sub>2</sub> releases (Xu et al., 2017). The OLS approach has been extended in this way. Only the predicted variable's conditional expectation may be provided by this technique, which does not offer a complete picture of a conditional distribution (mean value) (Lin & Xu, 2017). The quantile regression permits the coefficients to fluctuate over numerous quantiles and helps correct errors that might significantly impact estimating precision, such as unobserved heterogeneity, heteroscedasticity, and outliers (Koenker, 2005; Koenker & Hallock, 2001). The conditional quantile function of the panel data is addressed in the following econometric model (Koenker, 2004).

$$Q(\tau x_{\rm gt}) = \frac{x}{it} \beta(\tau) + \alpha_g + \varepsilon_{\rm gt}$$
(4)

In Eq. (4),  $\tau$  indicates the quantile,  $Q_{\text{yit}}(\tau x_{\text{it}})$  denote the  $\tau$ th quantile of the predicted variable; individual effects and the independent variable vector are represented by the  $x_{\text{gt}}$  and  $\alpha_g$ , respectively;  $\beta(\tau)$  indicates the parameter of regression of the  $\tau$ th quantile, and this could be calculated through the formula below;

$$\beta(\tau) = \operatorname{argmin}_{\beta_{(\tau)}} \sum_{h=1}^{q} \sum_{t=1}^{p} \sum_{g=1}^{s} \left( \left| y_{gt} - \alpha_g - \frac{x}{gt} \beta(\tau) \right| w_{gt} \right)$$
(5)

where the quantiles, years, and cities are represented by q, P, and S, respectively. Further, Wgt is the weight of the gth city in the tth year that is persistent with the piecewise linear quantile loss function. This method was developed by Koenker and Bassett (1978). The weight could be described as;

If

$$y_{\rm gt} - \alpha_g - x_{\rm gt}^{'} \beta(\tau) 0 \tag{6}$$

Then  $w_{\rm gt} = \tau$ .

If

$$y_{\rm gt} - \alpha_g - x'_{\rm gt} \beta(\tau) > 0 \tag{7}$$

Then  $w_{gt} = 1 - \tau$ .

This study pursues the action of Koenker (2004) and assigned 0.25, 0.5, and 0.75, correspondingly to the quartiles of  $\tau$ . The other technique is the panel spatial correlation consistent least-squares dummy variables (PSCC-LSDV) approach that has been employed. The period lag of the regressors was employed to adjust for inverse causality and endogeneity in the PSCC standard errors. Following Driscoll and Kraay (1998), this estimator employed a robust standard error method. Estimates of likely dependency have been made by readjusting the standard errors of the coefficient (Cameron & Trivedi, 2005; Hoechle, 2007). Fixing heterogeneities across panels by employing a dummy variable is a valuable use of the LSDV approach, sometimes known as the "fixed effects". It is easier to comprehend the fixed effects when using the least-squares dummy variable technique (Baum, 2013; Torres-Reyna, 2007). Thus, the panel spatial correlation consistent least-squares dummy variables (PSCC-LSDV) and panel quantile regression (PQR) have been preferred. The recent study has used two models to examine the environmental impact and ecological footprints. The first model is extracted from Waheed et al. (2018) by adding variables like non-renewable energy consumption, financial development, domestic investment, and economic growth for the case of BRICS economies. So, we have extended this model as follows:

$$\ln \text{CO}_{2\,\text{it}} = \ln \varphi_0 + \varphi_1 \ln \text{REC}_{\text{it}} + \varphi_2 \ln \text{non} \text{REC}_{\text{it}} + \varphi_3 \ln \text{FR}_{\text{it}} + \varphi_4 \ln \text{GDPC}_{\text{it}} + \varphi_5 \ln \text{DI}_{\text{it}} + \varphi_6 \ln \text{AP}_{\text{it}} + \varphi_7 \ln \text{FD}_{\text{it}} + \epsilon_{\text{it}}$$
(8)

The other model has been taken with ecological footprints as a dependent variable, and the remaining variables are the same with the same proxies as mentioned. The second model is,

$$\ln EF_{it} = \ln \varphi_0 + \varphi_1 \ln REC_{it} + \varphi_2 \ln \operatorname{non} REC_{it} + \varphi_3 \ln FR_{it} + \varphi_4 \ln GDPC_{it} + \varphi_5 \ln DI_{it} + \varphi_6 \ln AP_{it} + \varphi_7 \ln FD_{it} + \epsilon_{it}$$
(9)

Models (8) and (9) calculate  $CO_2$  emissions in metric tonnes per person and EF ecological footprints in global hectares per person, respectively. A percentage of GDP is used to quantify forest rents, referred to as FR. AP stands for agricultural products utilised in agriculture, forestry, and fisheries, with a constant 2015 US dollar value. Consumption of clean and renewable energy (REC) is expressed as a percentage of total final energy consumption, while nonREC refers to the electricity generated from fossil fuels (oil, gas, and coal) (per cent of total). GDPC, on the other hand, is the gross domestic product measured in 2015 dollars at a constant price level. FD stands for the financial development index, while DI is for domestic investment, assessed in constant 2015 US dollars by gross fixed capital formation. Due to the limited data availability, the BRICS economies were examined between 1995 and 2017. Global Footprint Network and the International Monetary Fund have been combed for the data on ecological footprint and the financial development index, respectively. The World Bank's World Development Indicators were used to get the data for the other variables.

#### 5 Results and discussion

This analysis is based on balanced panel data for BRICS economies from 1995 to 2017. The correlation matrix and descriptive statistics of Model 1 are given in Table 1 and 2, respectively. Mean, median, and mode show the central tendency of data. Skewness and kurtosis show the skewness of the data, whether the data are positively skewed or negatively skewed. Domestic investment is positively skewed, and the other variables are negatively skewed. All factors except renewable energy use and domestic investment positively correlate with carbon emissions.

Moreover, the descriptive statistics and correlation matrix of Model 2 are described in Table 1 and 3. All variables are negatively skewed except domestic investment, which is positively skewed. The correlation matrix explained that ecological footprint positively correlates with all variables, excluding domestic investment and non-renewable and renewable energy consumption.

The consequences of PSCC-LSDV and the PQR are mentioned in Table 4 for model 1. The outcomes of PSCC-LSDV indicate that renewable energy consumption, agriculture production, and financial development negatively affect CO<sub>2</sub> secretions. While on the other side, non-renewable energy consumption, forest rents, GDPC, and domestic investment have a significant and positive effect on CO<sub>2</sub> releases. These variables cause an upsurge in CO<sub>2</sub> emissions. The 1% rise in renewable energy consumption reduces the CO<sub>2</sub> by 0.3779 per cent, and the results are consistent with Baloch et al. (2019); Dong et al. (2017), and Wang and Dong (2019). The same increase in non-renewable energy consumption significantly increases CO<sub>2</sub> release by 0.2552 per cent, and the results are comparable with Anwar et al. (2021); Dogan (2016), and Shafiei and Salim (2014). The reason behind energy consumption is that it raises environmental degeneration through the consumption of fossil fuels like coal, gas, and oil. So, it makes the environment polluted through manufacturing goods because they are produced by the pollution-intensive inputs used by energy-intensive industries (Suri & Chapman, 1998).

The forest rents also cause a rise in the  $CO_2$  discharge significantly. The results are contrary to those of Waheed et al. (2018). The 1 per cent increase in forest rents raises the  $CO_2$  emission by 0.0917 per cent. The "land use change" theory supports these findings. According to the land use change hypothesis, when forests are removed for commercial activities such as agriculture, mining, or urbanisation, the carbon contained in trees is released into the atmosphere and contributes to greenhouse gas emissions.

Additionally, the loss of forests may disturb the natural carbon sequestration process, reducing the carbon flux from the atmosphere to the terrestrial environment. This may increase the total carbon flow from the terrestrial ecosystem to the atmosphere and increase carbon emissions (Houghton & Hackler, 2003). Furthermore, there is no other method to instantly grow trees after removing these trees; therefore, the carbon-absorbing capacity of nature decreases, leading to a rise in carbon emissions. (Miner, 2010). However, the 1 per cent rise in GDPC increases the CO<sub>2</sub> discharge by 0.3143 per cent. The result is consistent with those Shafiei and Salim (2014); Sulaiman and Abdul-Rahim (2017), and Zakarya et al. (2015). The quick rise in economic growth unlocks more opportunities to contribute to the economy, for instance, production, investment, and consumption that upsurge the water, soil, and air pollution (Baloch et al., 2019; Suri & Chapman, 1998). Similarly, the 1 per cent increase in domestic investment significantly increases the CO<sub>2</sub> discharge by 0.2104 per cent. The result corresponds to Liu et al. (2019).

| Table 1 Desci | riptive statistics of | model 1   |          |          |           |          |          |          |            |
|---------------|-----------------------|-----------|----------|----------|-----------|----------|----------|----------|------------|
| Variables     | InCO2                 | lnEF      | InREC    | InNONREC | InFR      | lnGDPc   | InDI     | lnAP     | lnFD       |
| Mean          | 1.323894              | 0.950913  | 2.858359 | 3.980447 | -0.911678 | 8.343245 | 26.33372 | 7.501893 | -0.755750  |
| Median        | 1.590470              | 1.088340  | 2.896630 | 4.382230 | -0.870501 | 8.643420 | 26.31680 | 8.270650 | -0.755023  |
| Maximum       | 2.454440              | 1.763060  | 3.997910 | 4.556110 | 0.209415  | 9.370020 | 29.32720 | 9.484170 | - 0.446287 |
| Minimum       | -0.262875             | -0.215218 | 1.163240 | 1.595030 | -2.335610 | 6.427080 | 24.04130 | 4.239570 | -1.272970  |
| Std. Dev      | 0.875167              | 0.575149  | 0.973970 | 0.831921 | 0.568299  | 0.838086 | 1.283353 | 1.713179 | 0.188759   |
|               |                       |           |          |          |           |          |          |          |            |

|          | lnCO2     | InREC     | InnonREC  | lnFR      | lnGDPC    | lnDI      | lnAP     | lnFD |
|----------|-----------|-----------|-----------|-----------|-----------|-----------|----------|------|
| lnCO2    | 1         |           |           |           |           |           |          |      |
| InREC    | -0.923509 | 1         |           |           |           |           |          |      |
| InnonREC | 0.355039  | -0.398780 | 1         |           |           |           |          |      |
| lnFR     | 0.094936  | -0.006414 | -0.148099 | 1         |           |           |          |      |
| lnGDPC   | 0.697775  | -0.567466 | -0.380523 | 0.118239  | 1         |           |          |      |
| lnDI     | -0.126562 | 0.080679  | -0.014048 | -0.869053 | -0.025101 | 1         |          |      |
| lnAP     | 0.213918  | -0.257131 | -0.274565 | 0.632152  | 0.406929  | -0.724610 | 1        |      |
| lnFD     | 0.354095  | -0.195244 | -0.052265 | -0.056038 | 0.545783  | 0.086597  | 0.246694 | 1    |

 Table 2
 Correlation matrix of model 1

**Table 3** Correlation matrix of model 2

|          | lnEF      | lnREC     | InnonREC  | lnFR      | lnGDPC    | lnDI      | lnAP     | lnFD |
|----------|-----------|-----------|-----------|-----------|-----------|-----------|----------|------|
| lnEF     | 1         |           |           |           |           |           |          |      |
| InREC    | -0.781699 | 1         |           |           |           |           |          |      |
| InnonREC | -0.126813 | -0.398780 | 1         |           |           |           |          |      |
| lnFR     | 0.155617  | -0.006414 | -0.148099 | 1         |           |           |          |      |
| lnGDPC   | 0.934852  | -0.567466 | -0.380523 | 0.118239  | 1         |           |          |      |
| lnDI     | -0.096615 | 0.080679  | -0.014048 | -0.869053 | -0.025101 | 1         |          |      |
| lnAP     | 0.343749  | -0.257131 | -0.274565 | 0.632152  | 0.406929  | -0.724610 | 1        |      |
| lnFD     | 0.390429  | -0.195244 | -0.052265 | -0.056038 | 0.545783  | 0.086597  | 0.246694 | 1    |

 Table 4
 PSCC-LSDV & panel quantile regression of model 1

| DV: InCO2 |            |            |            |            |  |  |  |
|-----------|------------|------------|------------|------------|--|--|--|
| Variables | PSCC-LSDV  | q.25       | q.5        | q.75       |  |  |  |
| InREC     | -0.3779*** | -0.3559*** | -0.3753*** | -0.3964*** |  |  |  |
|           | (0.001)    | (0.000)    | (0.000)    | (0.000)    |  |  |  |
| InnonREC  | 0.2552***  | 0.2725***  | 0.2571***  | 0.2405***  |  |  |  |
|           | (0.001)    | (0.000)    | (0.000)    | (0.000)    |  |  |  |
| lnFR      | 0.0917***  | 0.0971***  | 0.0923***  | 0.0871***  |  |  |  |
|           | (.008)     | (0.000)    | (0.000)    | (0.000)    |  |  |  |
| lnGDPpc   | 0.3143***  | 0.3081***  | 0.3136***  | 0.3195***  |  |  |  |
|           | (0.006)    | (0.000)    | (0.000)    | (0.000)    |  |  |  |
| lnDI      | 0.2104**   | 0.2201***  | 0.2115***  | 0.2023***  |  |  |  |
|           | (0.011)    | (0.000)    | (0.000)    | (0.000)    |  |  |  |
| lnAP      | -0.1442*** | -0.1537*** | -0.1453*** | -0.1363*** |  |  |  |
|           | (0.002)    | (0.000)    | (0.000)    | (0.000)    |  |  |  |
| lnFD      | -0.1573*   | -0.1429*** | -0.1557*** | -0.1695*** |  |  |  |
|           | (0.086)    | (0.009)    | (0.000)    | (0.005)    |  |  |  |

p < 0.1, p < 0.05, p < 0.01

However, the 1 per cent intensification in agricultural production significantly lessens the CO<sub>2</sub> discharge by 0.1442 per cent. The result is consistent with Koshta et al. (2020) and Rahman et al. (2020) and indicates that BRICS economies control CO<sub>2</sub> secretion from agricultural production. This finding might be due to carbon sequestration in agroforestry systems, which suggests that integrating trees into crop and livestock farming systems can lead to carbon sequestration and ultimately reduce carbon emissions. This notion is backed by the fact that agroforestry systems can store carbon in tree biomass and the soil via enhanced soil health and decreased erosion. Further, BRICS might be doing organic farming (Waheed et al., 2018) because if soil organic matter is high, it will further improve soil fertility and ability to absorb carbon emissions (Paustian et al., 1998).

Further, purveying solar tube wells for the small peasants for irrigation and tunnel farming is also beneficial to curb environmental degradation (Waheed et al., 2018). Financial development also helps to reduce  $CO_2$  emissions. The 0.1573 per cent reduction in  $CO_2$ emissions is due to a 1% increase in financial development, and the outcomes are consistent with Shahbaz et al. (2013). The environmental benefits of financial development support the green finance hypothesis, which states that as a nation's financial system grows and becomes more sophisticated, it is better equipped to channel funds towards investments in clean energy and other environmentally friendly initiatives. In turn, this may contribute to a decrease in carbon emissions.

Moreover, in panel quantile estimation, the coefficients fall into three categories of  $CO_2$ emissions: quarters (q25), half (q50), and three-quarters (q75). Low CO2 emitters are represented by the 25th percentile model (q25), medium  $CO_2$  emitters are represented by the 50th percentile model (q50), and high CO<sub>2</sub> emitters are represented by the 75th percentile model (q75).  $CO_2$  emissions are reduced as a result of the use of renewable energy. At the 25th, 50th, and 75th percentiles, the coefficients of "lnREC" are -0.3559, -0.3753, and -0.3964. CO<sub>2</sub> reduction from "lnREC" is said to be at its greatest for sources with large  $CO_2$  outputs. The InnonREC is caused by rising  $CO_2$  emanations. The coefficients of InnonREC are 0.2725, 0.2571, and 0.2405, which depict that every 1 per cent increase in the non-renewable energy consumption causes to upsurge by 0.2725 per cent in low emitters with positive influence and that is, sluggishly lessening in high emitters. The case is the same for forest rents. The coefficient of "InFR" is 0.0971, 0.0923, and 0.0871 at the 25th, 50th, and 75th percentiles. LnFR positively and significantly contributes to the rise of  $CO_2$  emissions, especially in low emitters, by 0.0971 per cent, while its influence continuously reduces in the intermediate and high emitters. The InGDPC contributed to the rise of  $CO_2$  emission positively and significantly. At the 25th, 50th, and 75th percentiles, the lnG-DPC coefficients are 0.3081, 0.3136, and 0.3195, respectively (see Table 1). It seems that InGDPC causes the highest concentrations of  $CO_2$  in high emitters.

The effect of domestic investment is positive and significant on  $CO_2$  emanations. The coefficients of domestic investment are 0.2201, 0.2115, and 0.2023, respectively, which shows that its effect in low emitters is high while its influence is gradually decreasing till in high emitters on  $CO_2$  discharges. Agriculture production shows that it has more influence on the reduction of  $CO_2$  in low emitters, and its reduction becomes gradually low while reaching high emitters according to the coefficients, which are -0.1537, -0.1453, and -0.1363, respectively. The coefficients of the financial development are -0.1429, -0.1557, and -0.1695, corresponding, indicating that a 1 per cent increase in financial development causes to decrease the  $CO_2$  emissions by 0.1429 per cent in low emitters, and it has more influence on high emitters for lessening  $CO_2$  emanations.

Further, the outcomes of the second model, ecological footprint, for PSCC-LSDV and panel quantile regression are in Table 5. The results of PSCC-LSDV depict that renewable

| DV: lnEF  |            |            |            |            |  |  |  |
|-----------|------------|------------|------------|------------|--|--|--|
| Variables | PSCC-LSDV  | q.25       | q.5        | q.75       |  |  |  |
| lnREC     | -0.2051*** | -0.1764*** | -0.2071*** | -0.2343*** |  |  |  |
|           | (0.002)    | (0.001)    | (0.000)    | (0.000)    |  |  |  |
| InnonREC  | 0.0018     | 0.0118     | 0.0010     | 0.0084     |  |  |  |
|           | (0.942)    | (0.712)    | (0.958)    | (0.736)    |  |  |  |
| lnFR      | 0.02839*   | 0.0427**   | 0.0273**   | 0.0137     |  |  |  |
|           | (0.077)    | (0.047)    | (0.049)    | (0.408)    |  |  |  |
| lnGDPpc   | 0.3043***  | 0.3282***  | 0.3026***  | 0.2800***  |  |  |  |
|           | (0.001)    | (0.000)    | (0.000)    | (0.000)    |  |  |  |
| lnDI      | 0.07487**  | 0.0881**   | 0.0739***  | 0.0614**   |  |  |  |
|           | (0.015)    | (0.015)    | (0.001)    | (0.028)    |  |  |  |
| lnAP      | -0.0771**  | -0.0860*** | -0.0764*** | -0.0680*** |  |  |  |
|           | (0.013)    | (0.000)    | (0.000)    | (0.000)    |  |  |  |
| lnFD      | -0.1851*** | -0.2152*** | -0.1830*** | -0.1545*** |  |  |  |
|           | (0.004)    | (0.000)    | (0.000)    | (0.000)    |  |  |  |

Table 5 PSCC-LSDV & panel quantile regression of model 2

p < 0.1, p < 0.05, p < 0.01

energy consumption has a significant and negative influence on ecological footprint. The 1% rise in renewable energy consumption lessens the ecological footprint by 0.2051 per cent. The outcomes are correlated with those Baloch et al. (2019); Khalid et al. (2021); Khan et al. (2021), and Wang and Dong (2019). In contrast, non-renewable energy consumption instigates the ecological footprint but not significantly.

A 1% rise in non-renewable energy consumption caused an insignificant rise in ecological footprint by 0.0018 per cent; the results are erratic to Destek and Sinha (2020). The 1 per cent upsurge in forest rents significantly raises the ecological footprint by 0.02839 per cent, according to Ahmed et al. (2020). The 1 per cent rise in GDPC increases ecological footprint by 0.3043 per cent, consistent with Nathaniel et al., (2020a, 2020b). Domestic investment causes to rise in ecological footprint; that is, a 1 per cent escalation in domestic investment significantly reduces the ecological footprint by 0.07487 per cent. So, the quality of the environment could also be improved by attracting investors. If more people were investing domestically, it would boost the activities of R&D, productivity, and investment in green technology (Hamdan et al., 2018). Although the 1 per cent rise in agricultural production significantly reduces the ecological footprint by 0.0771 per cent, the results contradict Niccolucci et al. (2008). Likewise, a one per cent surge in financial development significantly lessens the ecological footprint by 0.1851 per cent, which is consistent with Iftikhar Yasin et al. (2020) but contrary to I. Yasin et al. (2022). They argued that financial development boosts innovative and green technologies, reducing the cost of business and improving the environment by reducing pollution emissions. The 25th percentile model (q25) represents low ecological footprints, the 50th percentile model (q50) indicates medium ecological footprints, and the 75th percentile model (q75) specifies high ecological footprints.

On the other side, the outcomes of the PQR show that a 1 per cent increase in renewable energy consumption decreases the ecological footprint by 0.1764%, 0.2071%, and 0.2343% in low, medium, and high percentiles, respectively. The reduction of ecological footprints is maximal in the higher quartile of the ecological footprint. In contrast, non-renewable

energy consumption causes an increase in the ecological footprint. The coefficients are 0.0118, 0.0010, and 0.0084 at the 25th, 5th, and 75th percentiles accordingly, and its effect is more in low quartiles of ecological footprint, which becomes gradually low until it reaches high quartiles but not significantly. The forest rents, InGDPC, and domestic investment have increasing and significant effects on ecological footprints. The coefficients of forest rents are 0.0427, 0.0273, and 0.0137, respectively, indicating that the 1% increase in the forest rents causes an increase in the ecological footprints in the low quartile by 0.0427%. It becomes steadily declines when it reaches its high quartile. The coefficients of InGDPC are 0.3282 in the low quartile, 0.3026 in the medium quartile, and 0.2800 in the high quartile. It tells that the InGDPC increases the ecological footprint more in the low quartile and gradually decreases in the medium and high quartile.

Likewise, the coefficients of domestic investment are 0.0881 in the 25th quartile, 0.0739 in the 50th quartile, and 0.0614 in the 75th quartile, depicting that a 1% upsurge in domestic investment raises the ecological footprints by 0.0881% in low quartile and it becomes lower in middle and high quartiles. Further, agriculture production and financial development negatively and significantly influence ecological footprints. The coefficients of the agricultural production are -0.0860, -0.0764, and -0.0680 in the low, middle, and high quartiles, respectively, and it shows a steady diminution in the low to high quartiles of the ecological footprint. That means a 1 per cent surge in agriculture production lessens the ecological footprint by 0.086% in the low quartile. Similarly, the rise in financial development decreases the ecological footprint by 0.2152% in the low, 0.0183% in the medium, and 0.1545% in the high quartiles, and the value of the coefficients is little by little lower in the high quartile of the ecological footprint.

#### 6 Conclusion and recommendation policy

Overall, agricultural production, renewable energy consumption, and financial development help reduce the carbon emanation in BRICS economies. In contrast, non-renewable energy consumption, forest rents, domestic investment, and GDPC are not favourable for reducing carbon secretion. Furthermore, renewable energy consumption, financial development, and agricultural production are favourable to lessen the ecological footprint. Whereas forest rents, GDPC is damaging ecological footprint. Non-renewable energy consumption damages the environment by causing an ecological footprint, but not significantly.

For consistent and sustained growth by minimising environmental and ecological effects, the BRICS economies must devise a plan and implement policies encouraging investment in novel renewable energy technologies. Additionally, forestation and agricultural production should aid in addressing the issue of carbon emissions. Furthermore, financial development in BRICS economies is environmentally benign, so policies should be formulated to promote financial development.

**Data availability** The data used in this research are accessible through the Global Footprint Network and World Bank's WDI.

## Declarations

Conflict of interest There are no conflict of interests to declare.

## References

- Ahillen, S. (2016). Forest fires burn 119,000 acres in 8 Southeastern states. Retrieved from USA Today: https://www.usatoday.com/story/news/nation-now/2016/11/20/forest-fires-burn-119000-acres-8-south eastern-states/94169774.
- Ahmed, Z., Asghar, M. M., Malik, M. N., & Nawaz, K. (2020). Moving towards a sustainable environment: the dynamic linkage between natural resources, human capital, urbanization, economic growth, and ecological footprint in China. *Resources Policy*, 67, 101677.
- Ahmed, K. (2017). Revisiting the role of financial development for energy-growth-trade nexus in BRICS economies. *Energy*, 128, 487–495.
- Alola, A. A., Adebayo, T. S., & Onifade, S. T. (2022). Examining the dynamics of ecological footprint in China with spectral granger causality and quantile-on-quantile approaches. *International Journal of Sustainable Development & World Ecology*, 29(3), 263–276.
- Alvarado, R., Ortiz, C., Jiménez, N., Ochoa-Jiménez, D., & Tillaguango, B. (2021). Ecological footprint, air quality and research and development: The role of agriculture and international trade. *Journal of Cleaner Production*, 288, 125589.
- Ansari, M. A. (2022). Re-visiting the Environmental Kuznets curve for ASEAN: A comparison between ecological footprint and carbon dioxide emissions. *Renewable and Sustainable Energy Reviews*, 168, 112867.
- Anwar, A., Siddique, M., Dogan, E., & Sharif, A. (2021). The moderating role of renewable and non-renewable energy in environment-income nexus for ASEAN countries: Evidence from method of moments quantile regression. *Renewable Energy*, 164, 956–967.
- Atmadja, S., & Verchot, L. J. M. (2012). A review of the state of research, policies and strategies in addressing leakage from reducing emissions from deforestation and forest degradation (REDD+). *Mitigation* and Adaptation Strategies for Global Change, 17, 311–336.
- Azam, M. (2019). Relationship between energy, investment, human capital, environment, and economic growth in four BRICS countries. *Environmental Science and Pollution Research*, 26(33), 34388–34400.
- Azevedo, V. G., Sartori, S., & Campos, L. M. (2018). CO2 emissions: A quantitative analysis among the BRICS nations. *Renewable and Sustainable Energy Reviews*, 81, 107–115.
- Baccini, A., Goetz, S., Walker, W., Laporte, N., Sun, M., Sulla-Menashe, D., & Friedl, M. (2012). Estimated carbon dioxide emissions from tropical deforestation improved by carbon-density maps. *Nature Climate Change*, 2(3), 182–185.
- Baloch, M. A., Mahmood, N., & Zhang, J. W. (2019). Effect of natural resources, renewable energy and economic development on CO<sub>2</sub> emissions in BRICS countries. *Science of the Total Environment*, 678, 632–638.
- Baum, C. F. (2013). Panel data management, estimation and forecasting. 9.
- Bogoni, J. A., Graipel, M. E., & Peroni, N. J. (2018). The ecological footprint of Acca sellowiana domestication maintains the residual vertebrate diversity in threatened highlands of Atlantic Forest. PLoS ONE, 13(4), e0195199.
- Cameron, A. C., & Trivedi, P. K. (2005). Microeconometrics: Methods and applications. Cambridge University Press.
- Charfeddine, L. J. (2017). The impact of energy consumption and economic development on Ecological footprint and CO<sub>2</sub> emissions: Evidence from a Markov switching equilibrium correction model. *Energy Economics*, 65, 355–374.
- Dale, V. H., Joyce, L. A., McNulty, S., Neilson, R. P., Ayres, M. P., Flannigan, M. D., & Peterson, C. J. (2001). Climate change and forest disturbances: Climate change can affect forests by altering the frequency, intensity, duration, and timing of fire, drought, introduced species, insect and pathogen outbreaks, hurricanes, windstorms, ice storms, or landslides. *BioScience*, 51(9), 723–734.
- Destek, M. A., & Sinha, A. J. (2020). Renewable, non-renewable energy consumption, economic growth, trade openness and ecological footprint: Evidence from organisation for economic Co-operation and development countries. *Journal of Cleaner Production*, 242, 118537.
- Diesendorf, M. J. E. E. (2002). I= PAT or I= PBAT?, 42(1-2), 3-3.
- Dietz, T., & Rosa, E. A. (1997). Effects of population and affluence on CO<sub>2</sub> emissions. *Proceedings of the National Academy of Sciences*, 94(1), 175–179.

- Dogan, E., & Fahri, S. (2016). Determinants of CO<sub>2</sub> emissions in the European Union: The role of renewable and non-renewable energy. *Renewable Energy*, 94, 429–439.
- Dong, K., Sun, R., & Hochman, G. J. E. (2017). Do natural gas and renewable energy consumption lead to less CO<sub>2</sub> emission? *Empirical Evidence from a Panel of BRICS Countries.*, 141, 1466–1478.
- Driscoll, J. C., & Kraay, A. C. (1998). Consistent covariance matrix estimation with spatially dependent panel data. *Review of Economics and Statistics*, 80(4), 549–560.
- Ehrlich, P. R., & Holdren, J. P. (1971). Impact of population growth: Complacency concerning this component of man's predicament is unjustified and counterproductive. *Science*, 171(3977), 1212–1217.
- Gauli, B., & Upadhyay, S. (2013). Reducing emissions from deforestation and forest degradation (REDD) in Nepal: A review. *The Initiation*, 5, 75–83.
- Hamdan, R., Ab-Rahim, R., & Fah, S. S. (2018). Financial development and environmental degradation in ASEAN-5. International Journal of Academic Research in Business and Social Sciences, 8(12), 14–32.
- Harrison, P., & Pearce, F. (2000). AAAS atlas of population & environment. Univ of California Press.
- Hashmi, N. I., Alam, N., Jahanger, A., Yasin, I., Murshed, M., & Khudoykulov, K. (2023). Can financial globalization and good governance help turning emerging economies carbon neutral? Evidence from members of the BRICS-T. *Environmental Science and Pollution Research*, 30, 1–16.
- Hoechle, D. (2007). Robust standard errors for panel regressions with cross-sectional dependence. *The Stata Journal*, 7(3), 281–312.
- Holly, M. A., Larson, R. A., Powell, J. M., Ruark, M. D., & Aguirre-Villegas, H. (2017). Greenhouse gas and ammonia emissions from digested and separated dairy manure during storage and after land application. Agriculture, Ecosystems & Environment, 239, 410–419.
- Houghton, R., & Hackler, J. (2003). Sources and sinks of carbon from land-use change in China. Global Biogeochemical Cycles, 17(2).
- Irfan, M., Cherian, J., Rahman, A. A. A., Haddad, A. M., Sial, M. S., Ali, B., & Brugni, T. V. (2022). Measuring the impact of air pollutants on ecological footprint, forest area and cropland. *International Journal of Energy Economics and Policy*, 12(1), 444–452.
- Kang, Y., Khan, S., & Ma, X. (2009). Climate change impacts on crop yield, crop water productivity and food security–a review. *Progress in Natural Science*, 19(12), 1665–1674.
- Khalid, K., Usman, M., & Mehdi, M. A. (2021). The determinants of environmental quality in the SAARC region: A spatial heterogeneous panel data approach. *Environmental Science and Pollution Research*, 28(6), 6422–6436.
- Khan, I., Hou, F., & Le, H. P. (2021). The impact of natural resources, energy consumption, and population growth on environmental quality: Fresh evidence from the United States of America. Science of the Total Environment, 754, 142222.
- Koenker, R., & Bassett, G. (1978). Regression quantiles. Econometrica Journal of the Econometric Society, 33–50.
- Koenker, R. (2005). Quantile regression. Cambridge University Press.
- Koenker, R., & Hallock, K. F. (2001). Quantile regression. Journal of Economic Perspectives, 15(4), 143–156.
- Koenker, R. (2004). Quantile regression for longitudinal data. Journal of Multivariate Analysis, 91(1), 74–89.
- Koshta, N., Bashir, H. A., & Samad, T. A. (2020). Foreign trade, financial development, agriculture, energy consumption and CO2 emission: Testing EKC among emerging economies. *Indian Growth* and Development Review.
- Lin, B., & Xu, B. (2017). Which provinces should pay more attention to CO<sub>2</sub> emissions? Using the quantile regression to investigate China's manufacturing industry. *Journal of Cleaner Production*, 164, 980–993.
- Liu, Y., Gao, Y., & Hao, Y. (2019). Gospel or disaster? An empirical study on the environmental influences of domestic investment in China. *Journal of Cleaner Production*, 218, 930–942.
- Liu, Y., Sohail, M. T., Khan, A., & Majeed, M. T. (2022). Environmental benefit of clean energy consumption: Can BRICS economies achieve environmental sustainability through human capital? *Environmental Science and Pollution Research*, 29(5), 6766–6776.
- Magadza, C. H. (2000). Climate change impacts and human settlements in Africa: Prospects for adaptation. *Environmental Monitoring and Assessment*, 61(1), 193–205.
- Mead, D. J. (2005). Forests for energy and the role of planted trees. BPTS, 24(5–6), 407–421.
- Mehmood, U. (2022). Determining the factors of ecological footprints in South Asian countries: Exploring the role of renewable energy and forest area. *Environmental Science and Pollution Research*, 29, 1–8.

- Menon, S., Denman, K. L., Brasseur, G., Chidthaisong, A., Ciais, P., Cox, P. M., Holland, E. (2007). Couplings between changes in the climate system and biogeochemistry. Retrieved from
- Miner, R. (2010). Impact of the global forest industry on atmospheric greenhouse gases. Food and Agriculture Organization of the United Nations (FAO).
- Nathaniel, S., & Khan, S. A. R. (2020). The nexus between urbanization, renewable energy, trade, and ecological footprint in ASEAN countries. *Journal of Cleaner Production*, 272, 122709.
- Nathaniel, S., Anyanwu, O., & Shah, M. (2020). Renewable energy, urbanization, and ecological footprint in the Middle East and North Africa region. *Environmental Science and Pollution Research*, 27, 1–13.
- Nguyen, C. P., Le, T.-H., Schinckus, C., & Su, T. D. (2020). Determinants of agricultural emissions: panel data evidence from a global sample. *Environment and Development Economics* 1–22.
- Niccolucci, V., Galli, A., Kitzes, J., Pulselli, R. M., Borsa, S., & Marchettini, N. J. A. (2008). Ecological footprint analysis applied to the production of two Italian wines. *Ecosystems & Environment*, 128(3), 162–166.
- Pata, U. K. (2021). Linking renewable energy, globalization, agriculture, CO<sub>2</sub> emissions and ecological footprint in BRIC countries: A sustainability perspective. *Renewable Energy*, 173, 197–208.
- Paustian, K., Cole, C. V., Sauerbeck, D., & Sampson, N. (1998). CO<sub>2</sub> mitigation by agriculture: An overview. *Climatic Change*, 40(1), 135–162.
- Rahman, M. H., Majumder, S. C., & Debbarman, S. (2020). Examine the role of agriculture to mitigate the Co<sub>2</sub> emission in Bangladesh. *Asian Journal of Agriculture and Rural Development*, 10(1), 392–405.
- Raskin, P. D. (1995). Methods for estimating the population contribution to environmental change. *Ecological Economics*, 15(3), 225–233.
- Rees, W. E. (1992). Ecological footprints and appropriated carrying capacity: what urban economics leaves out. *Environment and urbanization*, 4(2), 121–130.
- Rees, W., & Wackernagel, M. (2008). Urban ecological footprints: why cities cannot be sustainable and why they are a key to sustainability. In Urban ecology (pp. 537–555): Springer.
- Roca, J. (2002). The IPAT formula and its limitations. Ecological Economics, 42(1-2), 1-2.
- Schulze, P. C (2002). I= PBAT. 40(2), 149–150.
- Shafiei, S., & Salim, R. A. (2014). Non-renewable and renewable energy consumption and CO<sub>2</sub> emissions in OECD countries: A comparative analysis. *Energy Policy*, 66, 547–556.
- Shahbaz, M., Solarin, S. A., Mahmood, H., & Arouri, M. J. E. M. (2013). Does financial development reduce CO<sub>2</sub> emissions in Malaysian economy? A *Time Series Analysis*, 35, 145–152.
- Stern, P. C., Young, O. R., & Druckman, D. E. (1992). Global environmental change: Understanding the human dimensions. National Academy Press.
- Stern, N. (2008). The economics of climate change. American Economic Review, 98(2), 1-37.
- Sulaiman, C., & Abdul-Rahim, A. S. (2017). The relationship between CO<sub>2</sub> emission, energy consumption and economic growth in Malaysia: A three-way linkage approach. *Environmental Science and Pollution Research*, 24(32), 25204–25220.
- Suri, V., & Chapman, D. (1998). Economic growth, trade and energy: Implications for the environmental Kuznets curve. *Ecological Economics*, 25(2), 195–208.
- Torres-Reyna, O. (2007). Panel data analysis fixed and random effects using Stata (v. 4.2). Data & Statistical Services, Priceton University, 112, 49.
- Tuna, G. (2022). The impact of biomass energy consumption on CO<sub>2</sub> emission and ecological footprint: The evidence from BRICS countries. *International Journal of Environmental Research*, 16(4), 1–15.
- Wackernagel, M., & Rees, W. (1998). Our ecological footprint: Reducing human impact on the earth (Vol. 9): New society publishers.
- Waggoner, P. E., & Ausubel, J. H. (2002). A framework for sustainability science: A renovated IPAT identity. Proceedings of the National Academy of Sciences, 99(12), 7860–7865.
- Waheed, R., Chang, D., Sarwar, S., & Chen, W. (2018). Forest, agriculture, renewable energy, and CO<sub>2</sub> emission. *Journal of Cleaner Production*, 172, 4231–4238.
- Wang, J., & Dong, K. (2019). What drives environmental degradation? Evidence from 14 Sub-Saharan African countries. Science of the Total Environment, 656, 165–173.
- Wenlong, Z., Nawaz, M. A., Sibghatullah, A., Ullah, S. E., Chupradit, S., & Minh Hieu, V. (2022). Impact of coal rents, transportation, electricity consumption, and economic globalization on ecological footprint in the USA. *Environmental Science and Pollution Research*, 1–16.
- Xu, R., Xu, L., & Xu, B. (2017). Assessing CO<sub>2</sub> emissions in China's iron and steel industry: Evidence from quantile regression approach. *Journal of Cleaner Production*, 152, 259–270.

- Yasin, I., Ahmad, N., & Chaudhary, M. A. (2020). Catechizing the environmental-impression of urbanization, financial development, and political institutions: A circumstance of ecological footprints in 110 developed and less-developed countries. *Social Indicators Research*, 147(2), 621–649.
- Yasin, I., Aslam, A., Siddik, A. B., Abbass, K., & Murshed, M. (2023). Offshoring the scarring causes and effects of environmental challenges faced by the advanced world: An empirical evidence. *Envi*ronmental Science and Pollution Research, 1–11.
- Yasin, I., Ahmad, N., & Chaudhary, M. A. (2021). The impact of financial development, political institutions, and urbanization on environmental degradation: Evidence from 59 less-developed economies. *Environment, Development and Sustainability*, 23(5), 6698–6721.
- Yasin, I., Naseem, S., Anwar, M. A., Madni, G. R., Mahmood, H., & Murshed, M. (2022). An analysis of the environmental impacts of ethnic diversity, financial development, economic growth, urbanization, and energy consumption: Fresh evidence from less-developed countries. *Environmental Science and Pollution Research International*, 29(52), 79306–79319. https://doi.org/10.1007/s11356-022-21295-7
- York, R., Rosa, E. A., & Dietz, T. (2002). Bridging environmental science with environmental policy: Plasticity of population, affluence, and technology. *Social Science Quarterly*, 83(1), 18–34.
- York, R., Rosa, E. A., & Dietz, T. J. (2003). Footprints on the earth: The environmental consequences of modernity. *American Sociological Review* 279–300.
- Zakarya, G. Y., Mostefa, B., Abbes, S. M., & Seghir, G. M. (2015). Factors affecting CO<sub>2</sub> emissions in the BRICS countries: A panel data analysis. *Proceedia Economics and Finance*, 26, 114–125.
- Zaman, K., Abdullah, I., & Ali, M. (2017). Decomposing the linkages between energy consumption, air pollution, climate change, and natural resource depletion in P akistan. *Environmental Progress & Sustainable Energy*, 36(2), 638–648.
- Zhang, Y.-J., & Wang, W. (2019). Do renewable energy consumption and service industry development contribute to CO 2 emissions reduction in BRICS countries? *Environmental Science and Pollution Research*, 26(31), 31632–31643.

**Publisher's Note** Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Springer Nature or its licensor (e.g. a society or other partner) holds exclusive rights to this article under a publishing agreement with the author(s) or other rightsholder(s); author self-archiving of the accepted manuscript version of this article is solely governed by the terms of such publishing agreement and applicable law.

# **Authors and Affiliations**

#### Iftikhar Yasin<sup>1</sup> · Nawaz Ahmad<sup>1</sup> · Saqib Amin<sup>2</sup> · Nyla Sattar<sup>1</sup> · Afsheen Hashmat<sup>1</sup>

☑ Iftikhar Yasin iftikharyasin@gmail.com

> Nawaz Ahmad nawazecon74@gmail.com

Saqib Amin saqib.amin@oulu.fi

Nyla Sattar nylasattar27@gmail.com

Afsheen Hashmat afsheenhashmat@gmail.com

- <sup>1</sup> Department of Economics, The University of Lahore, Lahore, Pakistan
- <sup>2</sup> Oulu Business School, University of Oulu, 90570 Oulu, Finland