RESEARCH ARTICLE

Investigating the impact of human capital on the ecological footprint in India: An empirical analysis

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Abstract

Many recent studies have focused on the influencing factors of the ecological footprint, but less attention has been given to human capital. Human capital, which is based on education and rate of return on education, may reduce the ecological footprint since environmental issues are human-induced. The current study investigates the impact of human capital on the ecological footprint in India for the period 1971 to 2014. The outcomes of the newly developed combined cointegration test of Bayer and Hanck disclose the long-run equilibrium relationship between variables. The findings reveal a significant negative contribution of human capital to the ecological footprint. The results of the causality test show that human capital Granger causes the ecological footprint without any feedback. In addition, energy consumption adds to the ecological footprint, while the relationship between economic growth and ecological footprint follows an inverted U-shaped pattern. The findings unveil the potential to reduce the ecological footprint by developing human capital.

Keywords Human capital in India · Ecological footprint · Bayer and Hanck cointegration test · Energy consumption · Neutrality hypothesis

Introduction

Anthropogenic activities impose a major threat to Earth's ecosystem, which has been providing us with fresh water, food, clean air, energy, and recreation. Human consumption of Earth's natural resources has surpassed the availability of natural resources (biocapacity), and we currently require the regenerative capacity of 1.6 Earths to fulfill our needs of ecological services. The upsurge in human demands, for instance, food, water, energy, infrastructure, and other exert ecological pressure which leads to resource depletion, emission of waste, land use changes, and pollution (WWF 2016; Rudolph and Figge 2017). Wackernagel and Rees (1996) introduced the concept of ecological footprint (EFP) to measure the aggregate pressure of human consumption on the biosphere.

The calculation of the ecological footprint is based on six land use categories to track the pressure of human consumption on our ecosystem, namely grazing land for livestock, forest land, cropland (food and fiber requirement), ocean, carbon footprint (forest required for CO_2 uptake), and buildup land (human infrastructure development). In more simple words, the ecological footprint is expressed in global hectares (gha), and it measures the geographically productive area and water necessary to support the human's consumption and to sequester the waste they generate under prevailing management practices and technology (Lin et al. 2016). According to the Global Footprint Network, our ecological demands for resource consumption and waste absorption have already exceeded the productive capacity of our planet. Consequently, we have been living in a state of ecological overshoot since 1970, which can cause environmental degradation, resource depletion, and even collapse of the biosphere (Ewing et al. 2010).

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In the majority of environmental studies, CO_2 emissions are used as an indicator of environmental degradation, but it only represents a small part of environmental degradation (Al-Mulali et al. 2015). The ecological footprint is a globally comparable, comprehensive, and reliable indicator of environmental impact, and it has recently been preferred over the CO_2 emissions because it can reveal the impact of human activities on the ecosystem in terms of soil, air, and water (Al-Mulali and Ozturk 2015; Charfeddine and Mrabet 2017; Uddin et al. 2017; Solarin et al. 2018; Ahmed et al. 2019b; Danish et al. 2019).

The objective of the current research is to investigate the impact of human capital on the ecological footprint in India. Human capital is based on years of schooling and return to education, and it is defined as skills and knowledge acquired by a person to enhance his productivity (Xing 2016; Danish et al. 2019). In more simple words, it is a combination of education and expected returns to education. Undeniably, previous literature provides enough evidence to believe that human capital stimulates economic growth (Haldar and Mallik 2010; Asghar et al. 2012; Alaali et al. 2015; Jandhyala Viswanath and Vishwanath 2015; Shukla 2017). The relationship between human capital and environment is not much discussed in the previous literature, but education may influence the environment through different channels.

According to United Nations Educational, Scientific, and Cultural Organization (UNESCO) publications, the climate change is linked to human activities, and education can help in identification of the causes and consequences of climate change and their mitigation (UNESCO 2007, 2010). Climate science involves complex scientific terms, and education increases access to various sources of information which enables an individual to understand unfamiliar and complex environmental issues. Education also increases the willingness to install renewable energy products (Chankrajang and Muttarak 2017). Zen et al. (2014) argue that people with high income and high educational background participate more in recycling activities as compared to individuals with low income and low educational background. Improper waste management practices can cause water contamination and environmental pollution.

Xu et al. (2012) suggest a linkage between education and pro-environmental practices. The authors report a positive impact of education on Chinese individual's preference to spend more on premium eco-labeled seafood for sea species sustainability. Bano et al. (2018) argue that human capital increases productivity, energy efficiency, and willingness to adopt green technologies in industries, household, and transportation. Likewise, Lan et al. (2012) disclose that human capital enhances technological capabilities which improve environmental quality by adopting green technology. Desha et al. (2015) suggest that skilled and educated human capital prefers to follow environmental laws. Moreover, according to Godoy et al. (1998), education has a negative relationship with

deforestation. Deforestation increases soil erosion and reduces CO_2 absorption and biodiversity. Therefore, reduction in deforestation can mitigate the ecological footprint and improve environmental quality. In short, human capital can reduce the ecological footprint by promoting pro-environmental practices, for instance water saving, recycling, energy efficiency, adoption of green technology, reduction in deforestation, eco-labeled food consumption, and others.

We selected India for our study due to several reasons. For instance, the human capital report 2015 issued by the World Economic Forum has ranked India just above the bottom 20 countries in terms of its human capital. India has been ranked 100 out of 124 countries, below neighboring countries, for instance Sri Lanka (no. 60), Bangladesh (no. 99), Iran (no. 80), and Bhutan (no. 87) (World Economic Forum 2015). The worsening situation of human capital in India discloses that human capital development has mostly been ignored in the national policies. India has tremendous potential for its human capital development as compared to developed nations, considering the rapid economic growth and huge population. Climate change is human-induced, and progress is needed on multiple fronts. Policies that ignore human capital (education and skills) cannot provide a holistic approach to combat this challenge.

Also, India is the third largest economy (in terms of 2010 PPP $), the second most populous country, and the fourth fastest growing economy with a massive growth rate of 7.6% (Shukla 2017). India is already the world's second largest energy consumer, and there are strong growth projections for the next several decades, which can further intensify energy consumption (U.S. Energy Information Administration 2018). The ecological footprint of India stood at 1.12 global hectares per capita in 2014 as compared to the biocapacity (availability of resources) of 0.45 global hectares per capita, indicating an ecological deficit of more than 140% (GFN 2018). It is an indication that the consumption of natural resources has exceeded the availability of natural resources in India. The massive resource consumption exerts environmental pressure resulting in climate change, and the shocks are felt in the form of melting glaciers in the Indian Himalayas, altering rivers' flow rates, increasing landslides, depleting water reserves, and flooding (Global Footprint Network 2008). India is committed to accomplish the Sustainable Development Goals (SDGs) by 2030. The SDGs involve in improving the standard of life of the people by providing them accommodation, quality education, access to energy, and other resources as well as ensuring a clean environment. The findings of the current study will help authorities to prioritize SDGs by considering their environmental viability and also use the potential mitigation options such as human capital development.

The contribution of this research is twofold. Firstly, to the best of our knowledge, this is the first study that analyzes the relationship between human capital and the environment in the context of India. Secondly, we use the ecological footprint

of consumption as a dependent variable which is suitable to examine the ecological consequences of human capital, considering its comprehensiveness. Also, we employed the combined cointegration method developed by Bayer and Hanck to check the cointegration between our variables, and the results are verified by using the autoregressive distributed lag (ARDL) bound test. Finally, the vector error correction model (VECM) is applied to examine the direction of causality between variables.

The remaining of this study is in the following order: The "Literature review" section contains a detail of previous studies; the "Data and model construction" section provides a detail about variables under investigation, sources of data, and model construction; the econometric methodology is discussed in the "Econometric methodology" section; the "Results and discussion" section contains a detailed discussion of our results; and the last section concludes this work and suggests some policies.

Literature review

The objective of the study is to investigate the impact of human capital on EFP. Developing countries such as India are determined to achieve economic development, which, in turn, increases environmental degradation. Therefore, it has become a significant challenge to achieve economic growth without stimulating ecological footprints. In order to achieve sustainable economic development, countries are exploring different options that could increase economic development as well as reduce environmental problems. In this regard, human capital, which has mostly been ignored in the previous literature, can provide a vital option to stimulate economic growth and to reduce environmental issues.

As suggested by Shukla (2017), human capital promotes economic development. Salim et al. (2017) further argue that human capital reduces energy consumption. Desha et al. (2015) suggest that environmental regulations are more likely followed in the areas with skilled and educated human capital. Mahmood et al. (2019) disclose a negative effect of human capital on emissions in Pakistan. Likewise, Bano et al. (2018) disclose a mitigating effect of human capital on emissions in Pakistan. The relationship between human capital and EFP could not get the attention of scholars; however, Hassan et al. (2018) and Danish et al. (2019) are the exceptions. Hassan et al. (2018) use human capital as a control variable while examining the relationship between EFP and natural resources in Pakistan. The findings confirm the environmental Kuznets curve (EKC) and the presence of a positive linkage between EFP and natural resources. Also, the authors report an insignificant impact of human capital on EFP and a negative influence of urbanization on EFP. Similarly, Danish et al. (2019) suggest a positive contribution

of economic growth in increasing EFP while an insignificant effect of human capital on EFP in Pakistan.

Apart from this, numerous studies have analyzed the influencing factors of EFP. For example, Charfeddine and Mrabet (2017) employ fully modified ordinary least squares (FMOLS) and dynamic ordinary least squares (DOLS) methodology to explore the EKC hypothesis for 15 Middle East and North African (MENA) countries by including some socio-political indicators. They find a variation in the relationship between the ecological footprint and income in different panels. The findings confirm the EKC for the whole panel and oil-exporting sub-panel. However, in the non-oil-exporting panel, this relationship was U-shaped. The results further disclose that urbanization reduces EFP, whereas energy consumption increases EFP. Using a similar methodology, Uddin et al. (2017) include trade and financial development in the model to examine the linear relationship between income and EFP for a panel of 27 countries with the highest ecological footprint. They report a positive linkage between income and EFP, a negative influence of financial development, and an insignificant impact of trade on EFP.

In a country-specific study, Charfeddine (2017) found a U-shaped pattern between income and the ecological footprint in Qatar. The outcomes further disclose that trade openness, financial development, and electricity usage increase the ecological footprint. Mrabet et al. (2017) could not find the EKC hypothesis in Qatar. The findings confirm a positive effect of oil prices on the ecological footprint whereas a negative relationship between trade openness and the ecological footprint. Al-Mulali and Ozturk (2015) examine the factors behind environmental degradation in 14 MENA countries by using panel data and FMOL methodology. The findings reveal that energy consumption, trade, and urbanization are the major contributor to EFP, while political stability reduces EFP.

In a panel study, Destek et al. (2018) disclose a U-shaped curve between income and EFP and a negative effect of trade and renewable energy for the EU countries. Conversely, Wang et al. (2013) found no evidence of the EKC between income and the ecological footprint by using a global dataset of 150 countries. Solarin and Al-Mulali (2018) analyze the influence of FDI on EFP while controlling for urbanization and economic growth. The findings disclose that urbanization and economic growth are the main drivers of environmental problems. Apart from this, Rudolph and Figge (2017) argue that globalization influences the ecological footprint. The findings show a variation in the effect of different dimensions of globalization on EFP. Likewise, Figge et al. (2017) disclose that globalization influences the ecological footprint. Conversely, Ahmed et al. (2019b) report that globalization does not affect EFP in Malaysia, while energy consumption, economic growth, and financial development influence EFP. Solarin et al. (2018) and Jorgenson and Clark (2009) suggest that military spending stimulates the ecological footprint.

Katircioglu et al. (2018) confirm the EKC by including tourism in the model. The authors argue that tourism development can reduce the ecological footprint.

Summing up, previous studies have used EFP as a proxy of environmental degradation to analyze the impact of different factors; however, the relationship between human capital and EFP could not get the attention of scholars. Only a few studies have used human capital as a control variable while investigating the effect of different factors on EFP. As per our knowledge, none of the studies has examined the impact of human capital on EFP in India. Also, no study has so far investigated the drivers of EFP in India, which is facing several challenges such as growing EFP, low level of human capital, and enormous energy consumption. The current study addresses this gap in the literature and analyzes the link between human capital and EFP in India. Apart from this, economic growth, energy, urbanization, and trade openness are important drivers of EFP in the previous literature. Therefore, the current study includes these critical factors to avoid the potential issue of omitted variable bias.

Data and model construction

The objective of our study is to investigate the impact of human capital on the ecological footprint in India from 1971 to 2014. To achieve our objective, we use the ecological footprint of consumption per capita as a dependent variable because it has been considered a reliable and comprehensive environmental indicator to track the impact of anthropogenic activities on the biosphere (Ulucak and Bilgili 2018). It is a widely accepted environmental indicator in the area of social sciences, and is commonly used in policy reports of United Nations Environment Programme (UNEP) and World Wildlife Fund (WWF) (Rudolph and Figge 2017). We study the impact of human capital on EFP because education stimulates ecological awareness and increases pro-environmental practices (Chankrajang and Muttarak 2017). According to Mahmood et al. (2019) and Bano et al. (2018), human capital improves environmental quality.

Apart from this, we control some important influencing factors of EFP. For instance, economic growth is an important determinant of environmental degradation. It is believed that environmental issues are linked with the stage of economic development, and a high level of development may improve environmental quality (Apergis and Ozturk 2015; Ahmad et al. 2016). Energy consumption contributes to EFP, and urbanization reduces it (Charfeddine and Mrabet 2017). According to Al-Mulali and Ozturk (2015), trade openness and urbanization add to the ecological footprint. Ben and Ben (2015) suggest that trade openness influences the environment, and its impact depends upon the composition, scale,

and technique effect. Based on the above discussion, we developed the following model to achieve our objective:

$$\mathrm{LnEFP}_t = \lambda_0 + \lambda_1 \mathrm{Ln}G_t + \lambda_2 (\mathrm{Ln}G)_t^2 + \lambda_3 \mathrm{Ln}E_t$$
$$+ \lambda_4 \mathrm{Ln}C_t + \lambda_5 \mathrm{Ln}U_t + \lambda_6 \mathrm{Ln}T_t + \mu_t \quad (1)$$

In this equation, LnEFP indicates the ecological footprint of consumption per capita, $\mathrm{Ln}G$ represents economic growth (measured in per capita GDP), $\mathrm{Ln}G^2$ is the quadratic term of per capita GDP to verify the EKC hypothesis, $\mathrm{Ln}E$ is the energy consumption per capita, $\mathrm{Ln}C$ is the human capital, $\mathrm{Ln}T$ is the trade openness, $\mathrm{Ln}U$ is the urbanization, and μ_t refers to the error term. We used the human capital index as a proxy for human capital following some previous studies (Fang 2016; Fang and Chang 2016; Ulucak and Bilgili 2018). The human capital index is a comprehensive measure of human capital. It is based on years of schooling and rate of return for primary, secondary, and tertiary education. In the recent literature, a growing number of studies have preferred the human capital index as a measure of human capital (Hassan et al. 2018; Ulucak and Bilgili 2018; Danish et al. 2019; Mahmood et al. 2019). It is noteworthy that none of these studies have examined the effect of primary, secondary, and tertiary education on the environment, separately. We have not included primary or secondary education separately in our analysis following these scholars. Also, the World Bank's data on primary, secondary, and tertiary enrollment contains missing values, thus not suitable for reliable estimates.

We accessed the Penn World Table, version 9, which provides reliable data on human capital (Feenstra et al. 2015). Unlike the previous versions, it provides the data on years of schooling by comparing and combining the dataset of Barro and Lee (2013) and Cohen and Leker (2014), while the rate of returns to education is based on Mincer equation estimates (Psacharopoulos 1994). The website of Global Footprint Network is accessed to collect the data on the ecological footprint of consumption. The data on all other variables such as energy, economic growth, urbanization, and trade are amassed from the World Bank. Our research uses yearly data for the period 1971 to 2014, and the selected time frame is based on data availability. All variables are transformed into natural logarithm form for reliable estimates. It is important to reduce the chances of heteroscedasticity and to address normality (Bekhet and Othman 2017). Table 1 provides information about variables under investigation and data sources accessed.

Econometric methodology

We used cointegration and causality methods to investigate the influence of human capital on EFP. First of all, we

Table 1 Variables and data source

Variables used	Description	Data source
Ecological footprint of consumption (LnEFP)	It is measured in global hectares per capita	Global Footprint Network
Economic growth (LnG)	Per capita GDP measured in constant 2010 US \$	World Development Indicators
Quadratic term of GDP (LnG^2)	Quadratic term of GDP to check the nonlinear relationship	
Energy consumption (LnE)	Energy consumption measured as per capita kg of oil equivalent	World Development Indicators
Human capital (LnC)	The human capital index is used in the study, which is based on years of education and rate of return for primary, secondary, and tertiary education	Penn World Tables
Trade openness (LnT)	Sum of exports and imports (goods and services) as a percentage of GDP	World Development Indicators
Urbanization (LnU)	Urban population (percentage growth rate)	World Development Indicators

examined the unit root properties of our variables by employing a combination of conventional and structural break unit root tests. After determining the order of integration, we used the Bayer and Hanck cointegration test to examine the cointegration between our variables. The ARDL bound test is used to verify the results of cointegration. After confirmation of cointegration, the ARDL bound test is used to ascertain the short- and long-run dynamics, and the FMOLS, DOLS, and CCR estimators are employed to verify the results of the ARDL bound test. Finally, the VECM is used to analyze the direction of causality.

Unit root tests

Before the cointegration analysis, it is imperative to examine the order of integration. We employed the augmented Dickey-Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) unit root test to examine the order of integration. The augmented Dickey-Fuller test is based on the null hypothesis of non-stationary, whereas the Kwiatkowski-Phillips-Schmidt-Shin test has the alternative hypothesis of non-stationary and the null hypothesis of stationary. In the ADF test, the null hypothesis of non-stationary is rejected if the associated p values are below 0.10, 0.05, and 0.01.

Conversely, the KPSS test does not provide p values, and the decision is made by comparing the value of the computed Lagrange multiplier (LM) statistic with the critical values of the test. If the LM statistic goes beyond the critical values, we can reject the null hypothesis of stationary. However, the ADF and KPSS tests can provide biased estimates because of their inability to allow for any potential structural break (Shahbaz et al. 2015; Danish et al. 2017b). To overcome the shortcomings of conventional unit root tests, we employed the structural break unit root method proposed by Zivot and Andrews (1992) which determines the order of integration and provides information about possible structural breaks.

Cointegration analysis

There are several cointegration tests available in the literature to examine the long-run equilibrium relationship between our variables. For instance, Engle and Granger (1987) introduced

a residual-based cointegration test, which has widely been used in the literature. After the pioneering work of Engle and Granger (1987), many other cointegration tests were introduced, such as Johansen (1988) cointegration test, Johansen and Juselius (1990) cointegration test, Banerjee et al. (1998) ECM-based test, and Boswijk (1994) cointegration test. These tests are unreliable in case of a small sample and mixed order of integration. Further, different cointegration tests may generate different outcomes since no test is perfect and completely reliable (Chandran Govindaraju and Tang 2013). The conflicting results of individual tests may leave a researcher indecisive regarding the selection of a suitable cointegration test. Under this situation, we employed the recently developed, combined cointegration method of Bayer and Hanck (2013) and the ARDL bound test following Ahmed et al. (2019a, 2019b). The Bayer and Hanck test yields robust results and unambiguous test decision by combining previous cointegration tests. This method uses the following Fisher formula that combines the probability values of four cointegration methods:

$$\text{EG–JOH} = -2[\text{Ln}(P_{\text{EG}}) + \text{Ln}(P_{\text{JOH}})] \tag{2}$$

$$\begin{aligned} &\text{EG–JOH–BO–BDM} \\ &= -2[\text{Ln}(P_{\text{EG}}) + \text{Ln}(P_{\text{JOH}}) + \text{Ln}(P_{\text{BO}}) + \text{Ln}(P_{\text{BDM}})] \end{aligned} \tag{3}$$

In the above equations, EG and JOH indicate the probability values of famous Engle and Granger (1987) and Johansen (1991) cointegration tests, while BO and BDM represent the probability values of Boswijk (1994) and Banerjee et al. (1998). The null hypothesis is rejected when the Fisher statistic surpasses the critical values of Bayer and Hanck (2013).

We used the ARDL bound test to verify the outcomes of Bayer and Hanck test. The ARDL methodology has certain advantages over other cointegration techniques. This methodology generates efficient results with the small sample as in our case (Pesaran et al. 2001; Danish and Baloch 2017). It can be employed even if the variables are integrated at different orders,

for instance 1(0) or 1(1), or fractionally integrated. However, we cannot apply this methodology if any variable is integrated of 1(2) (Ahmed et al. 2019b). An appropriate modification in the lag order of the ARDL model is enough to avoid autocorrelation and endogeneity problem (Ahmed et al. 2019a). The ARDL methodology involves the estimation of the following unrestricted error correction model to determine the long-run and short-run dynamics, simultaneously:

$$
\begin{aligned}
\Delta(\mathrm{LnEFP})_t &= \alpha_0 + \sum_{k=1}^{P} \alpha_{1k}\Delta(\mathrm{LnEFP})_{t-k} + \sum_{k=0}^{P} \alpha_{2k}\Delta(\mathrm{LnEFP})_{t-k} + \sum_{k=0}^{P} \alpha_{3k}\Delta(\mathrm{LnG^2})_{t-k} \\
&+ \sum_{k=0}^{P} \alpha_{4k}\Delta(\mathrm{LnE})_{t-k} + \sum_{k=0}^{P} \alpha_{5k}\Delta(\mathrm{LnC})_{t-k} + \sum_{k=0}^{P} \alpha_{6k}\Delta(\mathrm{LnU})_{t-k} + \sum_{k=0}^{P} \alpha_{7k}\Delta(\mathrm{LnT})_{t-k} \\
&+ \alpha_1(\mathrm{LnEFP})_{t-1} + \alpha_2(\mathrm{LnG})_{t-1} + \alpha_3(\mathrm{LnG^2})_{t-1} + \alpha_4(\mathrm{LnE})_{t-1} + \alpha_5(\mathrm{LnC})_{t-1} \\
&+ \alpha_6(\mathrm{LnU})_{t-1} + \alpha_7(\mathrm{LnT})_{t-1} + \varepsilon_t
\end{aligned}
\tag{4}
$$

where p is the lag length, ε_t is the residual term, and Δ is used for the first difference operator. The first part of equations with the summation ($\sum$) sign indicates the short-run relationships, while the second part denotes the long-run relationships. The value of F statistics is compared with the critical values of Pesaran et al. (2001) or Narayan (2005) to determine the cointegration between variables. For Eq. 4 when the value of computed F statistics exceeds the upper critical bound (UCB), the null hypothesis of no cointegration ($H_0 : \alpha_1 = \alpha_2 = \alpha_3 = \alpha_4 = \alpha_5 = \alpha_6 = \alpha_7 = 0$) is rejected and the alternative hypothesis of cointegration ($H_1 : \alpha_1 \neq \alpha_2 \neq \alpha_3 \neq \alpha_4 \neq \alpha_5 \neq \alpha_6 \neq \alpha_7 \neq 0$) is accepted. In contrast, when the value of F statistics is smaller than the lower critical bound (LCB), it is an indication of no cointegration between the variables under investigation. Furthermore, we cannot make any decision for the existence of cointegration, if the value of computed F statistics comes between upper and lower critical bound values. We preferred the critical values of Narayan (2005) over Pesaran et al. (2001) because critical values of Narayan (2005) are based on 30 to 80 observations and are suitable for our small sample size of 44 observations.

After confirmation of cointegration, we estimated Eq. 4 to explore the long-run and short-run elasticities. Moving forward, various diagnostics tests were performed to ensure that our model is free from heteroskedasticity, serial correlation, and incorrect functional form. We also performed the cumulative sum (CUSUM) and cumulative sum of squares (CUSUMsq), the parameters stability tests suggested by Brown et al. (1975). We employed the DOLS, canonical cointegrating regression (CCR), and FMOLS estimators to verify the long-run results of the ARDL bound test. The DOLS estimator corrects for a possible endogeneity problem in the model and small sample bias. It can also be applied in the case of fractionally integrated variables (1(0) and 1(1)) (Masih and Masih 2000). Likewise, the FMOLS method accounts for autocorrelation and endogeneity problems.

VECM

Lastly, we used the vector error correction model to explore the direction of the relationship (causality) between variables. According to Granger (1988), when the variables are stationary at 1(1) and cointegrated, it becomes essential to employ the VECM for causality test. The policy recommendations require long-run elasticities as well as the causal direction between variables under investigation. The vector error correction model is specified below

$$
\begin{bmatrix}
\mathrm{LnEFP} \\
\mathrm{LnG} \\
\mathrm{LnG^2} \\
\mathrm{LnE} \\
\mathrm{LnC} \\
\mathrm{LnU} \\
\mathrm{LnT}
\end{bmatrix}
=
\begin{bmatrix}
\psi_1 \\
\psi_2 \\
\psi_3 \\
\psi_4 \\
\psi_5 \\
\psi_6 \\
\psi_7
\end{bmatrix}
+
\begin{bmatrix}
\psi_{11k} & \psi_{12k} & \psi_{13k} & \psi_{14k} & \psi_{15k} & \psi_{16k} & \psi_{17k} \\
\psi_{21k} & \psi_{22k} & \psi_{23k} & \psi_{24k} & \psi_{25k} & \psi_{26k} & \psi_{27k} \\
\psi_{31k} & \psi_{32k} & \psi_{33k} & \psi_{34k} & \psi_{35k} & \psi_{36k} & \psi_{37k} \\
\psi_{41k} & \psi_{42k} & \psi_{43k} & \psi_{44k} & \psi_{45k} & \psi_{46k} & \psi_{47k} \\
\psi_{51k} & \psi_{52k} & \psi_{53k} & \psi_{54k} & \psi_{55k} & \psi_{56k} & \psi_{57k} \\
\psi_{61k} & \psi_{62k} & \psi_{63k} & \psi_{64k} & \psi_{65k} & \psi_{66k} & \psi_{67k} \\
\psi_{71k} & \psi_{72k} & \psi_{73k} & \psi_{74k} & \psi_{75k} & \psi_{76k} & \psi_{77k}
\end{bmatrix}
\begin{bmatrix}
\Delta \mathrm{LnEFP} \\
\Delta \mathrm{LnG} \\
\Delta \mathrm{LnG^2} \\
\Delta \mathrm{LnE} \\
\Delta \mathrm{LnC} \\
\Delta \mathrm{LnU} \\
\Delta \mathrm{LnT}
\end{bmatrix}
\tag{5}
$$

$$
+
\begin{bmatrix}
\psi_1 \\
\psi_2 \\
\psi_3 \\
\psi_4 \\
\psi_5 \\
\psi_6 \\
\psi_7
\end{bmatrix}
(\mathrm{ECT}_{t-1}) +
\begin{bmatrix}
\mu_{1t} \\
\mu_{2t} \\
\mu_{3t} \\
\mu_{4t} \\
\mu_{5t} \\
\mu_{6t} \\
\mu_{7t}
\end{bmatrix}
$$

where ECT_{t-1} symbolizes the error correction term, μ_t is the disturbance term, and Δ represents the first difference operator. The negatively significant ECT depicts long-run causality. The short-run causal relationship is indicated by the significance of F statistics, and it is calculated by applying the Wald test to the differences and lagged difference of all predictors in the model.

Results and discussion

Descriptive statistics of the variables are summarized in Table 2 for the period 1971 to 2014. The variables are in logarithm form, LnEFP per capita ranges from -0.1987 to 0.0492 because of the lower level of human consumption in the early years and the significant increase in the later years. Human capital (LnC) ranges from 0.0754 to 0.3127. Economic growth (LnG) ranges from 3.21 2.54 to 3.21 because the GDP per capita of India has significantly increased over the year. The probability values of the Jarque-Bera normality test indicate the normality of data for all variables.

We employed a combination of unit root tests to investigate the unit root properties of our variables. The results of the ADF test in Table 3 disclose that the variables are non-stationary at levels as the probability values (0.99, 1.00, 1.00, 1.00, 0.83, 0.95, and 0.74) are not below 0.10. However, the variables under study become stationary at their first difference because the relevant p values are below 0.10. The human capital is significant at 5% level because its p value (0.04) is below 0.05, while all other variables are

Table 2 Descriptive statistics

	LnEFP	LnG	LnE	LnC	LnT	LnU
Mean	− 0.0989	2.7977	2.5725	0.1913	1.3260	0.4782
Median	− 0.0977	2.7452	2.5624	0.1883	1.2841	0.4525
Maximum	0.0492	3.2166	2.8044	0.3127	1.7465	0.5971
Minimum	− 0.1987	2.5461	2.4282	0.0754	0.8894	0.3702
SD	0.0707	0.2057	0.1105	0.0774	0.2514	0.0731
Jarque-Bera normality	2.5699	3.7850	2.8506	3.7138	2.6779	3.6231
Prob.	0.2767	0.1506	0.2404	0.1561	0.2621	0.1633

significant at 1% level (*p* values less than 0.01). The results of the KPSS test reveal that the values of LM statistics (0.81, 0.81, 0.81, 0.82, 0.83, 0.76, and 0.80) are above the 1% critical value (0.73). Therefore, the null hypothesis of stationary is rejected at level 1(0). It infers that our variables are non-stationary at levels. However, the null hypothesis of the KPSS test cannot be rejected at the difference where the LM statistics are below critical values under different significance levels. The results of both conventional unit root tests disclose that our variables are stationary at 1(1).

These conventional unit root tests can generate biased estimates because of their inability to allow for any possible structural break. To overcome this deficiency, we employed the Zivot and Andrews (1992) structural breaks unit root test. Table 4 shows the results of the unit root test with structural breaks, break years, and critical values. The results show that the variables are first difference stationary as the *t* values (− 4.67, − 4.62, − 7.16, − 4.83, − 4.94, and − 6.01) are less than critical values at different significance levels. The dependent variable has a structural break in 2004. Indian parliament enacted the Biological Diversity Act 2002 in February 2003 to conserve biodiversity and ensure sustainable use of its components (GOVT. 2002). This act and consequent rules may have exploited some environmental indicators in the

subsequent years. We excluded the dummy variable from our analysis since the dummy variable was insignificant, and the exclusion of dummy variable had no impact on our results. The overall results depict that the variables are integrated of 1(1); therefore, we can apply the combined cointegration test.

We employed the recently developed cointegration method of Bayer and Hanck to examine the existence of cointegration between our variables. Before the cointegration analysis, we determined the optimum lag length under the Schwarz-Bayesian criterion (SBC). Table 5 shows the results of combined cointegration tests. In Table 5, EG-JOH indicates the Fisher statistics based on Engle and Granger (1987) and Johansen (1988, 1991)) cointegration tests, whereas EG-JOH-BO-BDM is the Fisher statistics that also combines the *p* values of Boswijk (1994) and Banerjee et al. (1998) tests, in addition to Engle and Granger (1987) and Johansen (1988, 1991) cointegration tests. The value of Fisher statistics (16.71 and 86.00) exceeds the relevant 1% critical values (15.46 and 29.962) of Bayer and Hanck (2013). Thus, the null hypothesis of no cointegration has rejected under both tests.

Moving forward, we applied the ARDL bound test to verify these results. We used the SBC lag length 1 for our study, and it is determined under the VAR lag length criteria. The results of the bound test are summarized in Table 6. The

Table 3 Unit root tests

Variables	Augmented Dickey-Fuller (ADF)				KPSS	
	AT level		First difference		AT level	First difference
	t statistics	Prob.	*t* statistics	Prob.	LM statistics	LM statistics
LnEFP	1.0390	0.9963	− 8.8809*	0.0000	0.8127*	0.3793
LnG	3.7949	1.0000	− 5.8434*	0.0000	0.8180*	0.4412
LnG^2	4.6075	1.0000	− 5.1752*	0.0001	0.8116*	0.4589
LnE	3.7494	1.0000	− 4.8149*	0.0003	0.8277*	0.5726
LnC	− 0.7063	0.8341	− 2.0404**	0.0419	0.8373*	0.1708
LnU	− 0.0244	0.9509	− 7.2055*	0.0000	0.7691*	0.1547
LnT	− 0.9861	0.7499	− 5.3500*	0.0001	0.8097*	0.1052

Critical values of the KPSS test are 0.347 (10%), 0.463 (5%), and 0.739(1%)

*Significance level of 1%

**Significance level of 5%

Table 4 ZA unit root test

Variables	t value	p value	Structural break
LnEFP	− 2.9332	0.0087	2007
LnG	− 2.8064	0.1104	1979
LnE	− 2.9309	0.0010	2007
LnC	− 4.0520	0.0109	1996
LnU	− 4.4960	0.0000	2001
LnT	− 3.2551	0.0183	1981
ΔLnEFP	− 4.6797***	0.0710	2004
ΔLnG	− 4.6239***	0.0825	2005
ΔLnE	− 7.1619*	0.0123	2004
ΔLnC	− 4.8319***	0.0012	1996
ΔLnU	− 4.9460**	0.0000	2001
ΔLnT	− 6.0104*	0.0108	1988

Critical values are − 5.34 (1%), − 4.93 (5%), and − 4.58 (10%)

***Significance at 10% level

**Significance at 5% level

*Significance at 1% level

critical values of the bound test are reported in Table 7. The value of F statistics (5.74) is larger than the upper critical bound (5.12) of Narayan (2005) at 1% significance level when the ecological footprint of consumption is used as a dependent variable. It implies the rejection of the null hypothesis; therefore, the variables are cointegrated. Likewise, the values of F statistics (17.64, 19.90, 13.37, 7.42, 6.31, and 5.64) are more than the upper critical bound (5.12) when we used other dependent variables (LnG, LnG², LnC, LnU, and LnT). The results of the bound test strongly validate the results generated by the Bayer and Hack cointegration test. After confirmation of cointegration, we estimated Eq. 4 for the long-run and short-run elasticities.

Table 8 presents the long-run and short-run estimates of the ARDL bound test. The coefficient of human capital (LnC) is negatively significant at 1% level, which suggests that human capital mitigates the ecological footprint. A 1% increase in human capital will reduce EFP by 1.14%. This negative relationship is plausible because human capital is based on

schooling years and rate of return for education (primary, secondary, and tertiary) and education raises income level which allows people to install renewable energy sources. Education increases environmental awareness and stimulates pro-environmental practices, for example energy conservation, recycling, water saving, consumption of eco-labeled food, use of eco-labeled electric appliances, and contribution in emissions reduction policies (Clark and Finley 2007; Mills and Schleich 2012; Wijaya and Tezuka 2013; Xu et al. 2012; Zen et al. 2014). All such practices can negatively impact the ecological footprint. The negative linkage between human capital and EFP is a positive sign for India. The authorities can focus on human capital development to improve environmental quality, and India possesses huge potential for the human capital development since it has been ranked very low (100 out of 124 countries) in terms of its human capital (World Economic Forum 2015).

The coefficients of LnG and LnG² are statistically significant at 1% level with an elasticity of 2.48 and − 0.36, respectively. It implies that a 1% upsurge in per capita GDP (economic growth) will increase the ecological footprint by 2.18%, whereas a similar 1% increase in per capita GDP² will reduce the EFP by 0.36%. These results confirm an inverted U-shaped relationship between economic growth and the ecological footprint for India. Our finding is similar to that of Charfeddine and Mrabet (2017) for the MENA region. Likewise, Ahmad et al. (2016) have reported the EKC hypothesis for India by using CO_2 emissions as the dependent variable. This relationship can be explained on the ground that India's economy is growing at a rapid pace and the surge in economic growth has increased the use of resources, such as food, energy, water, and forest. India is the world's second largest energy consumer, and the majority of its energy needs are met by burning fossil fuels (U.S. Energy Information Administration 2018). Moreover, as a lower middle-income country, precedence is given to the economic development over the environment, resulting in a positive effect of income on EFP. However, our results suggest that a high level of income can reduce the ecological footprint. These findings are in consonance with the concept of the EKC hypothesis, which states that high-income level leads to environmental

Table 5 Bayer-Hanck cointegration test

Model	Fisher statistics		Cointegration
	EG-JOH	EG-JOH-BO-BDM	
(LnEFP/LnG, LnG², LnE, LnC, LnU, LnT)	16.7139*	86.0022*	✓
Critical values			
1% significance level	15.467	29.962	
5% significance level	10.352	19.761	
10% significance level	8.200	15.872	

*Significance level of 1%

Table 6 ARDL bound test for cointegration

Estimated models	F statistics	Lag order	Cointegration
(LnEFP/LnG, LnG^2, LnE, LnC, LnU, LnT)	5.7495*	[1,0,0,0,0,0]	✓
(LnG/LnEFP, LnG^2, LnE, LnC, LnU, LnT)	17.6469*	[1,0,1,0,0,0]	✓
(LnG^2/LnG, LnEFP, LnE, LnC, LnU, LnT)	19.9072*	[1,1,0,0,0,0]	✓
(LnE/LnG, LnG^2, LnEFP, LnC, LnU, LnT)	13.3733*	[1,0,0,0,0,0]	✓
(LnC/LnG, LnG^2, LnE, LnEFP, LnU, LnT)	7.4223*	[1,0,0,0,0,0]	✓
(LnU/LnG, LnG^2, LnE, LnC, LnEFP, LnT)	6.3123*	[1,0,0,0,1,0,0]	✓
(LnT/LnG, LnG^2, LnE, LnC, LnU, LnEFP)	5.6403*	[1,0,0,0,0,1,1]	✓

Optimum lag length 1 under the Schwarz-Bayesian criterion (SBC) is used

*Significance at 1% level

awareness, research and development, innovation, and use of green technology, which can reduce environmental problems.

The coefficient of energy consumption (LnE) is significant at 1% level, which suggests that energy consumption increases the ecological footprint of consumption. The previous studies have also reported a positive relationship between energy usage and EFP (Charfeddine and Mrabet 2017; Ahmed et al. 2019b). The positive effect of energy consumption is not surprising because energy consumption stimulates the carbon footprint, which constitutes approximately 51% of the total EFP in India.

Surprisingly, the coefficient of urbanization (LnU) is negatively significant, which suggests that urbanization reduces the ecological footprint in India. This result contradicts the scholars who report a positive influence of urbanization on environmental degradation (Al-Mulali and Ozturk 2015; Charfeddine 2017; Rashid et al. 2018). However, our finding is similar to those of Charfeddine and Ben Khediri (2016) and Sharma (2011). Urbanization can reduce the ecological footprint through several channels. Urbanization can improve productivity and resource efficiency by achieving economies of scale. It can promote the service sector, which is less harmful to the environment. In urban areas, public services, such as waste management, water supply, and sanitation, are economical to construct and operate. Furthermore, urbanization leads toward green technology, innovation, and energy efficiency (Charfeddine and Mrabet 2017). Finally, the results indicate an insignificant effect of trade on EFP. It implies that trade openness is not a determinant of EFP in India. This result is consistent with Uddin et al. (2017) who report the insignificant effect of trade openness on a panel of 27 countries with the highest ecological footprint. Sharma (2011) has also

disclosed an insignificant effect of trade openness on the environment for three income-based panels and a global panel of 69 countries.

In the short-run results, human capital reduces EFP, and the elasticity of the coefficient is 0.35. A 1% increase in human capital will mitigate EFP by 0.35%. Similarly, urbanization has a negative and significant coefficient which is consistent with our long-run finding. However, all other variables do not affect EFP. Also, we have not found the EKC hypothesis in the short-run. This outcome is supported by Ahmad et al. (2016) who could not confirm the EKC for India in the short-run path. The coefficient of ECT is negative (-0.81) and significant which implies that 81% of a deviation from long-run equilibrium is corrected in 1 year and it takes approximately 1 year and 2 months for overall adjustment. The negatively

Table 7 Critical values for the ARDL bound test

Critical values	LCB 1(0)	UCB 1(1)
1% significance	3.505	5.121
5% significance	2.618	3.863
10% significance	2.218	3.314

Table 8 Results of the ARDL bound test (estimated model = (LnEFP/LnG, LnG^2, LnE, LnC, LnU, LnT))

Variables	Coefficients	t statistics	Prob.
Long-run results			
LnG	2.4852*	3.0420	0.0044
LnG^2	-0.3678*	-2.8272	0.0077
LnE	0.5666*	3.0366	0.0045
LnC	-1.1487*	-4.2200	0.0002
LnU	-0.2586**	-2.6567	0.0118
LnT	-0.0095	-0.4035	0.6889
C	-5.2576*	-3.7884	0.0006
Short-run results			
LnG	0.3704	1.2242	0.2290
LnG^2	-0.0364	-1.2550	0.2178
LnE	-0.2511	-1.5745	0.2549
LnC	-0.3550***	-1.7682	0.0857
LnU	-0.1908***	-1.7263	0.0931
Log$T$	0.0453	1.3840	0.1751
CointEq(-1)	-0.8105*	-2.9105	0.0062

***Significance at 10%

**Significance at 5% level

*Significance at 1% level

Table 9 Results of the diagnostic tests

DW statistics	2.1721
R^2	0.9927
Adjusted R^2	0.9913
χ^2 arch	0.1201 [0.7229]
χ^2 LM	0.5175 [0.5200]
J-B normality	0.1117 [0.9456]
χ^2 reset	1.6462 [0.1877]

significant coefficient of the lagged ECT also indicates a strong cointegration relationship between variables under investigation (Saboori et al. 2012).

The diagnostic test statistics are reported in Table 9. The results suggest that our model is free from heteroskedasticity, serial correlation, and incorrect functional form. Moreover, the results of the J-B normality test indicate that the errors are normally distributed.

We employed the CUSUM and CUSUMsq approaches to investigate the stability of the regression coefficients. The results are reported in Figs. 1 and 2. The plotted lines of cumulative sum and cumulative sum of squares are within 5% critical bound, which indicates the stability of the coefficient in our model.

Moving forward, we used the DOLS, CCR, and FMOLS methods to corroborate the long-run estimates of the ARDL bound test following Danish et al. 2017a and Danish et al. 2018. The results reported in Table 10 suggest that economic growth (per capita GDP) increases EFP, whereas G^2 (quadratic term of per capita GDP) reduces EFP. Human capital and

urbanization lessen the EFP. Energy consumption adds to the ecological footprint, while trade openness is insignificant. The results of these three methods are in consonance with our previous results of the ARDL approach. Therefore, we can claim that the results of the ARDL bound test are reliable.

Finally, we used the VECM model to explore the causal linkage between our variables. The results are reported in Table 11. The ECT is negative and significant for only the ecological footprint, urbanization, and trade openness equations. It indicates that in case of any shock to EFP equation, 67% of the deviation is corrected in the first year, while in case of any shock to urbanization and trade openness equations, 12% and 22% of the deviations are corrected in the first year, respectively. It also suggests that deviations from the long-run equilibrium path are only corrected by the ecological footprint, urbanization, and trade openness. These negatively significant coefficients of lagged ECT show that economic growth, square of economic growth, energy consumption, and human capital Granger cause EFP, urbanization, and trade openness without any feedback. The feedback effect is found between EFP, urbanization, and trade openness.

Going into more detail, the long-run causality from human capital to EFP indicates that human capital reduces the ecological footprint. Likewise, human capital Granger causes urbanization, which implies that an increase in education leads to urbanization because people with quality education and skills move to urban areas for better employment. Energy consumption Granger causes EFP without any feedback. Unidirectional causality also runs from per capita GDP (economic growth) and the square of per capita GDP to EFP. This

Fig. 1 Plot of Cumulative Sum of Recursive Residuals
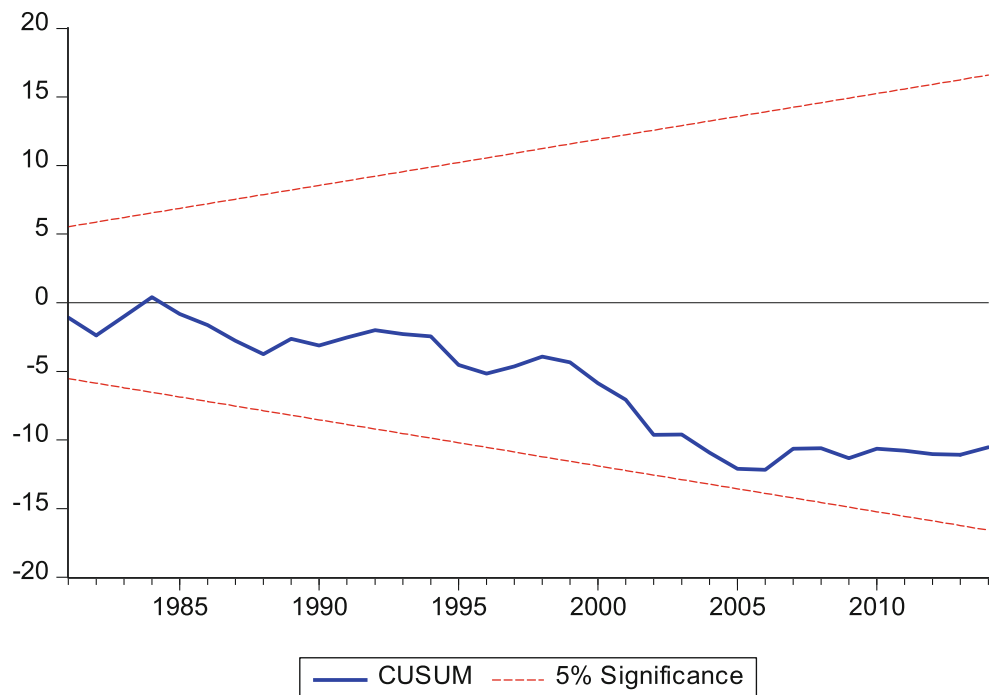
Fig. 2 Plot of Cumulative Sum of Squares of Recursive Residuals

Conclusion and policies
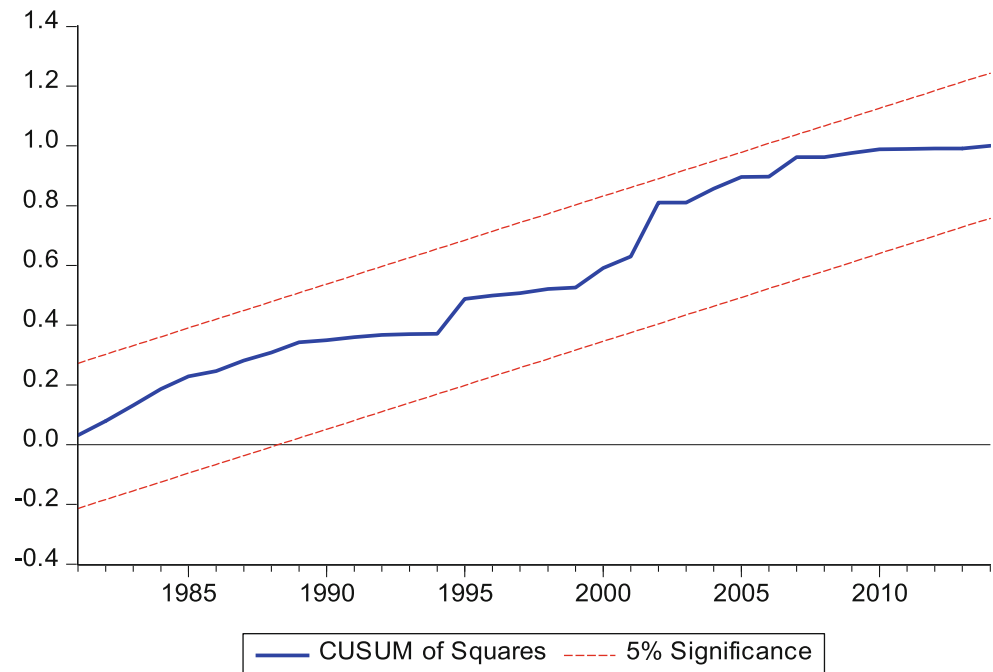
result is consistent with our finding of the EKC between economic growth and EFP. Interestingly, we have not found a causality between energy consumption and economic growth. This outcome supports the neutrality hypothesis, which infers that energy conservation policies may not hurt the economic development of India. The finding of the neutrality hypothesis is in line with Dogan (2015) for Turkey and Lee (2006) for Germany, Sweden, and the UK.

Turning to the short-run causality, human capital Granger causes EFP. Energy consumption causes economic growth, which indicates that economic growth relies on energy consumption, and in the short-run path, energy conservation can hamper economic growth. Further, economic growth (LnG) and its quadratic term (LnG^2) Granger cause human capital and trade openness. It suggests that economic development stimulates investment in human capital and also boosts trade.

This study analyzes the linkage between human capital and the ecological footprint. The results of conventional and structural break unit root tests show that our variables are stationary at 1(1). The results of Bayer and Hanck combined cointegration test disclose the cointegration between our variables, and the ARDL bound test is used to verify the results of the combined cointegration test. The long-run estimates of the ARDL bound test reveal a negative relationship between human capital and the ecological footprint, which implies that human capital improves the environment. The relationship between economic growth and EFP supports the EKC hypothesis. Energy consumption increases EFP, and urbanization reduces it. The DOLS, CCR, and FMOL techniques are employed to validate the long-run findings of the ARDL

Table 10 Results of the DOLS, FMOLS, and CCR methods

Variables	DOLS		Canonical cointegrating regression (CCR)		FMOLS	
	Coefficients	p values	Coefficients	p values	Coefficients	p values
LnG	2.1306*	0.0017	2.2928*	0.0000	2.2998*	0.0002
LnG^2	− 0.3252*	0.0030	− 0.3541*	0.0011	− 0.3576	0.0003
LnE	0.6840*	0.0000	0.7507*	0.0000	0.7689*	0.0000
LnC	− 0.9728*	0.0000	− 1.0389**	0.000	− 1.0289*	0.0000
LnU	− 0.1953**	0.0118	− 0.1784**	0.0163	− 0.1683**	0.0330
LnT	− 0.0063	0.7690	− 0.0075	0.7123	− 0.0056	0.7622
C	− 4.9726*	0.0001	− 5.3641	0.0000	− 5.4125*	0.0000

**Significance at 5%

*Significance at 1%

Table 11 The VECM Granger causality test

Dependent variables	LnEFP	LnG	LnG²	LnE	LnC	LnU	LnT	ECM$_{t-1}$
LnEFP	–	0.5231 [0.4695]	0.3942 [0.5301]	0.8500 [0.3565]	3.2086*** [0.0733]	2.2142 [0.1367]	1.5383 [0.2149]	−0.6763* [0.0027]
LnG	2.8638 [0.1001]	–	3.3257* [0.0720]	3.5706*** [0.0588]	0.2200 [0.6390]	0.4438 [0.5053]	0.2200 [0.6390]	0.0633 [0.9023]
LnG²	2.7565 [0.1063]	4.1192** [0.0424]	–	3.5400*** [0.0599]	0.2363 [0.6268]	0.3378 [0.5611]	2.0811 [0.1491]	−0.09616 [0.8132]
LnE	1.661 [0.1974]	1.832 [0.1758]	2.099 [0.1474]	–	0.5366 [0.4638]	0.1308 [0.7176]	1.1433 [0.2849]	0.1214 [0.2145]
LnC	0.2475 [0.6188]	5.8527** [0.0156]	5.7318* [0.0167]	1.7451 [0.1865]	–	1.0844 [0.2977]	0.4516 [0.5016]	−0.0546 [0.1150]
LnU	2.3317 [0.1268]	2.5671 [0.1091]	3.0780*** [0.0794]	1.9557 [0.1620]	1.1654 [0.2803]	–	0.1824 [0.6693]	−0.1293*** [0.0846]
LnT	0.0008 [0.9765]	3.4950*** [0.0616]	4.1482** [0.0417]	0.0538 [0.8165]	9.2233 [0.0024]	0.1387 [0.7095]	–	−0.2264* [0.0000]

***Significance at 10% level

**Significance at 5% level

*Significance at 1% level

bound test. Lastly, the results of the VECM show unidirectional causality from human capital to the ecological footprint both in the long-run and short-run.

These results have immense importance for the policymakers in the context of India. The authorities should invest more in human capital development projects because India has ranked among the bottom 30 countries by the human capital development report. Moreover, environmental awareness programs should be launched in the country to impart the general public about climate change and the importance of pro-environmental practices, for example energy saving, water saving, use of renewable energy products, and recycling. Environmental awareness programs can avail print and electronic media for more effective campaigns. The topics related to energy, environment, and global climate change should be included in the formal education syllabus to shape an environment-friendly society.

Our findings show a negative impact of urbanization on the ecological footprint, but current urbanization level is just 32%. Urban planning should focus on increasing the urban density along with associated infrastructure development, and compact cities should be designed to achieve resource efficiency. Energy consumption deteriorates environmental quality because of the large reliance on fossil fuels. The Government of India has already taken various initiatives to boost the renewable energy sector, and India is included among the countries with the largest renewable energy production. However, fossil fuels still represent almost 75% of total energy; therefore, more renewable energy projects should be launched because the country is enormously rich in renewable energy resources. Also, the neutrality hypothesis (in the long-run path) exists between energy consumption and economic growth; therefore, authorities can formulate various energy conservation policies to improve environmental quality in the long-run path.

Human capital is a broader concept which not only includes education and expected return to education but also health aspects. The current study has some limitations as it has analyzed only the impact of the human capital index (based on education on expected return) on the ecological footprint. Future studies can incorporate health aspects to form a more comprehensive human capital indicator. Also, future studies can analyze the disaggregate effect of primary, secondary, and tertiary education on the ecological footprint.

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