Revisiting the nexus of ecological footprint, human capital, total factor productivity, hydropower and growth in India: A multivariate approach

Javid Ahmad Khan, Sayed Gulzar Ganai and Mudasir Ahmad Sheergujree

Abstract

Purpose – *The purpose of this study is to investigate the impact of human capital, total factor productivity, hydropower consumption and economic growth on the ecological footprint in India from 1980–1981 to 2022–2023.*

Design/methodology/approach – *The stationarity of the data is examined using the augmented Dickey–Fuller, Phillips–Perron and Zivot–Andrews tests to account for potential structural breaks. The autoregressive distributed lag (ARDL) model is used to investigate long-run relationships and estimate the associated coefficients. Furthermore, Granger causality is examined within a vector error correction model (VECM) framework to determine the direction of causality and ensure the robustness of the results.*

Findings – *The major findings of the study demonstrate that human capital significantly reduces the ecological footprint via scale, technique and awareness effects. In contrast, total factor productivity significantly increases the ecological footprint, indicating that productivity gains prioritize economic efficiency over environmental sustainability in India. Hydropower consumption significantly increases the ecological footprint, and economic growth follows the environmental Kuznets curve pattern. The ecological footprint is found to be the most responsive variable in the system, driven by explanatory variables without reciprocal influence.*

Practical implications – *It is recommended that India embed sustainability into education and skill-building to harness human capital for ecological improvement. Technological advancement should balance economic and environmental efficiency by promoting clean, low-impact innovation over resource-intensive growth. Hydropower policy should prioritize small-scale projects, especially in fragile regions. A unified strategy integrating green productivity, renewable energy, education and ecological governance is vital for sustainable development in India.*

Originality/value – *To the best of the authors' knowledge, this is the first empirical study to incorporate total factor productivity into a long-run environmental sustainability model for India using the ecological footprint. It highlights the environmental costs of productivity-led growth. Future research should examine sectoral and regional variations for deeper insights.*

Keywords *Economic growth, Human capital, Hydropower, Total factor productivity, Ecological footprint, ARDL and Granger causality*

Paper type *Research paper*

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1. Introduction

In the face of intensifying climate change, environmental degradation and ecological fragility, sustainability has emerged as a central pillar of global development discourse. According to the OECD (2020), unchecked climate change could reduce global GDP by up to 10% by 2100, exacerbating critical challenges such as biodiversity loss, natural resource

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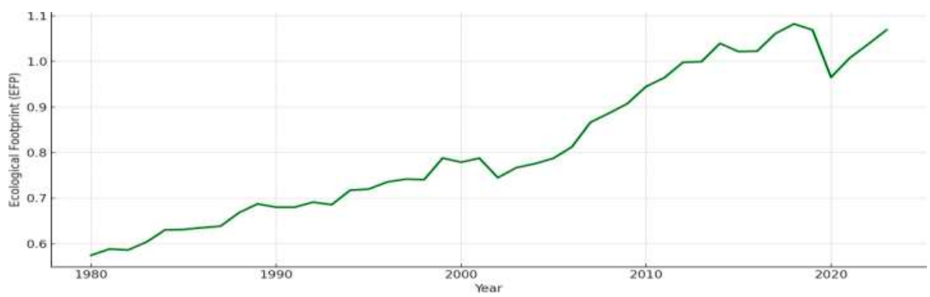
depletion and pollution (Wu *et al.*, 2018). Recognizing this, the United Nations' 2030 Agenda for sustainable development urges a transformative shift toward inclusive, resilient and environmentally conscious growth models. However, achieving this equilibrium demands a nuanced understanding of how various socioeconomic and technological drivers influence environmental quality, particularly in developing economies navigating rapid structural change. One of the most comprehensive and increasingly adopted metrics to evaluate environmental sustainability is the ecological footprint (EFP). Unlike CO_2 emissions, which capture only a portion of environmental degradation, the ecological footprint quantifies the total biologically productive land and water area required to produce consumed resources and absorb generated waste. When examined alongside bio-capacity, the ecological footprint offers a more integrated assessment of anthropogenic pressure on ecosystems (Global Footprint Network, 2023). This broader metric is particularly relevant for emerging economies, where environmental impacts extend beyond emissions to encompass land use, resource extraction and consumption patterns. Among the key variables influencing sustainability outcomes are human capital, total factor productivity (TFP), renewable energy consumption and economic growth, each interwoven into the broader environmental Kuznets curve (EKC) hypothesis. It is proposed that environmental degradation increases with income growth at early stages but begins to decline after reaching a certain income threshold, resulting in an inverted U-shaped relationship (Grossman and Krueger, 1995).

Human capital, defined as the aggregate of a population's education, skills, health and innovative capacity (Becker, 2002), is a foundational driver of economic progress. Rooted in endogenous (Romer, 1990; Mankiw *et al.*, 1992) growth theory, it improves labor productivity, enhances innovation diffusion and contributes to long-term development. While its economic benefits are well-documented (Barro, 1999; Aghion and Howitt, 1998; Khan *et al.*, 2022), its sustainability characteristics are empirically underexplored. Another critical but under-examined factor is TFP, widely accepted as a proxy for technological progress and efficiency improvements. In the neoclassical growth framework, TFP reflects output growth not explained by traditional inputs such as labor and capital. While early models (Solow, 1956) treated technology as exogenous, endogenous growth theories later emphasized the importance of human capital, research and development (R&D), innovation systems and institutional quality in driving TFP (Romer, 1990; Aghion and Howitt, 1998). In this context, TFP has the potential to decouple economic output from ecological degradation; yet, its direct influence on ecological footprint remains under-examined, especially in countries like India, where innovation is increasing but environmental outcomes lag. Within the energy–environment–growth nexus, renewable energy serves as a cornerstone for advancing Sustainable Development Goal 7, which advocates for clean and affordable energy, while simultaneously addressing environmental degradation. For developing economies like India, expanding energy access amidst rapid population growth presents a critical challenge: aligning rising energy demand with long-term sustainability.

India, as the world's second most populous country and one of the fastest-growing major economies, offers a compelling case for a multidimensional analysis of sustainability challenges. The post-1991 liberalization era brought accelerated economic growth, technological innovation and industrial expansion; however, this trajectory has simultaneously amplified environmental stress. Currently, India ranks third globally in total ecological footprint, contributing over 1.5 billion global hectares, while its bio-capacity is only 492 million global hectares, making it the sixth-largest ecological debtor (World Population Review, 2024). As depicted in Figure 1, there is a consistent rise in India's per capita ecological footprint from 1980–1981 to 2022–2023, highlighting growing anthropogenic pressure on natural ecosystems in India. A temporary dip in 2020, driven by the COVID-19-induced economic slowdown, is followed by a sharp rebound, reaffirming the long-term upward trend. Simultaneously, India's human capital remains underdeveloped, with a human capital index score of just 0.49 (World Bank, 2020a, 2020b), and persistent

Figure 1 Trend of ecological footprint per person in India (1980–2023)



Source: Authors' own work based on data from the Global Footprint Network (2024)

disparities in health, nutrition and education. On the productivity front, TFP growth has fluctuated between −2.8% and 3.3% during 1991–2019 (KLEMS database of Reserve Bank of India (RBI), 2022), signaling both progress and structural inefficiencies. Historically, hydropower played a dominant role, accounting for 37% of installed capacity and over 53% of electricity generation at the time of independence in 1947. Although its relative share diminished with the expansion of coal-based power from the late 1960s, hydropower remains integral to India's low-carbon energy transition. As of 2023, it constitutes approximately 11% of total installed capacity and 12.5% of electricity generation, complemented by 4,745.6 MW of operational pumped storage and 57,345 MW under development [Arto, 2016; International Renewable Energy Agency (IRENA), 2017]. Despite the growing recognition of sustainability as a multidimensional policy priority, empirical research remains limited in examining the interdependent roles of human capital, TFP, hydropower consumption (HPC) and economic growth in shaping ecological footprints – particularly within the Indian context. In response, this study investigates the central question: to what extent do human capital, TFP, HPC and economic growth influence ecological footprints in India, and can their interplay facilitate a transition toward sustainable development, as postulated by the EKC hypothesis? This research contributes to the existing literature and bridges critical gaps in four distinct ways. First, it uses the ecological footprint as a comprehensive indicator of environmental degradation, extending beyond conventional carbon-based metrics to capture the broader sustainability implications of human capital accumulation, TFP, HPC and growth dynamics. Second, it is, to the best of our knowledge, the first empirical study in the Indian context to evaluate the sustainability characteristics of technological progress using TFP as a proxy, and to examine its long-term influence on ecological outcomes. Third, the study is novel in its approach to assess the combined effects of human capital, TFP, HPC and economic growth, thereby offering a multidimensional perspective on the determinants of ecological stress in a rapidly developing economy. Fourth, the study advances the methodological frontier by applying robust time-series econometric techniques, including the autoregressive distributed lag (ARDL) bounds testing approach and the vector error correction model (VECM) Granger causality framework, to uncover both short-run dynamics and long-run equilibrium relationships among the variables. Together, these contributions offer a more holistic understanding of factors influencing ecological sustainability in India and provide policy-relevant insights for India's transition toward a greener growth path. Followed by the introduction as Section 1, the rest of the paper is structured as follows: Section 2 reviews the relevant literature; Section 3 outlines the theoretical framework, empirical model and methodology; Section 4 presents results and discussion; and Section 5 concludes with key findings, policy recommendations and limitations.

2. Review of literature

2.1 Economic growth and environmental quality

The nexus between economic growth and environmental degradation is central to environmental economics, particularly through the EKC hypothesis. Grossman and Krueger (1995) proposed that environmental degradation initially rises with income growth but declines after surpassing a certain threshold, forming an inverted U-shaped curve. While numerous studies support this hypothesis (Ghoshal and Bhattacharyya, 2008; Sinha and Bhattacharya, 2017; Ulucak and Lin, 2017; Danish *et al.*, 2019; Zafar *et al.*, 2019; Ahmad *et al.*, 2016; Alam and Adil, 2019; Kanjilal and Ghosh, 2013; Villanthenkodath *et al.*, 2021), its generality remains debated. Critics argue that the EKC may not hold across all contexts due to structural and institutional heterogeneity (Dietzenbacher and Mukhopadhyay, 2007). Pal and Mitra (2017) provide mixed evidence from India and China, indicating that regional and temporal factors influence the growth–emissions relationship. What seems to be common across these studies is the adoption of CO_2 emissions as the indicator for the environment, which may not be valid in all cases, especially when it comes to resource stocks (Ulucak and Lin, 2017). This study, while using the EKC, tries to evaluate the nexus through the ecological footprint rather than CO_2.

2.2 Energy consumption and environmental quality

GDP is the standard explanatory variable in most environmental studies, closely followed by energy consumption due to its significant emission impact. Although widely studied, the energy–CO_2 nexus shows mixed results across methods and sources. Several studies report a strong positive link between energy use and emissions (Feng, 2022; Shafiei and Salim, 2014; Menyah and Wolde-Rufael, 2010). In South Asia, Rahman and Kashem (2017) found energy use raised emissions in Bangladesh, while Vidyarthi (2013) and Nain *et al.* (2017) confirmed similar patterns in India and China. A growing literature supports the mitigating role of renewable energy. Anwar *et al.* (2021), Balsalobre-Lorente and Leitão (2020), Nathaniel *et al.* (2020) and Ikram *et al.* (2020) report that renewable energy significantly reduces emissions. However, Ahmed and Elfaki (2024a) suggested that outcomes may depend on technological readiness. Regarding the sources of renewable energy, solar energy offers strong mitigation effects (Kuşkaya, 2022; Kuşkaya *et al.*, 2023), while wind's impact remains mixed (Kuşkaya and Bilgili, 2020). Few studies investigating hydropower have found different results. Solarin *et al.* (2017) and Bello *et al.* (2018) find a negative link between hydroelectricity and CO_2 in China and India; others report negligible or mixed effects (Kartal *et al.*, 2023; Ummalla and Samal, 2018). Environmental costs such as greenhouse gas (GHG) emissions from reservoirs (Li *et al.*, 2015; Zhang *et al.*, 2015) and water losses (Gleick, 1993) further complicate the narrative. Adebayo *et al.* (2023) find hydropower reduces ecological footprints but only in the long run. Despite mixed global evidence on hydropower's environmental impact, its effect on ecological footprints in India remains understudied. Most Indian studies focus on CO_2 emissions, overlooking broader sustainability indicators. This study addresses this gap by examining hydropower's long-run influence on the ecological footprint.

2.3 Human capital and environmental quality

Human capital (HC) has gained prominence in environmental research, yet its impact on environmental outcomes, particularly CO_2 emissions, remains contested and context-specific. Studies such as Yao *et al.* (2019, 2021), Bano *et al.* (2018) and Zafar *et al.* (2019) suggest that higher education and skilled labor reduce emissions and support the EKC hypothesis. However, Hassan *et al.* (2019) found that human capital and bio-capacity worsened environmental quality in Pakistan. Khan *et al.* (2025a) show a long-run negative impact of human capital on ecological footprints in China and India, while their Indiafocused study (Khan *et al.*, 2026) links human capital to sustainability via mitigating urbanization impact on CO_2. Their findings reveal that building human capital induces a scale effect by boosting growth, a technique effect through the adoption of cleaner technologies and a behavioral effect by fostering environmental consciousness. Productivity-based studies (Ahmed and Krishnasamy, 2013a, 2013b; Ahmed, 2012a, 2012b) emphasize the role of human capital in cleaner growth in ASEAN and East Asia. In OECD nations, human capital is linked to lower CO_2 emissions (Yao *et al.*, 2020; Kim and Go, 2020; Goetz *et al.*, 1998), yet in Thailand, awareness gains failed to yield behavioral change (Chankrajang and Muttarak, 2017). Lan and Munro (2013) highlight the role of compliance mechanisms, while Du *et al.* (2022) and Cakar *et al.* (2021) show that HC may raise emissions in high-growth contexts. Rahman and Velayutham (2020) find environmental gains from HC without EKC validation. Despite growing interest, the impact of human capital on ecological footprints in India remains insufficiently explored. Existing studies offer mixed results, often limited to CO_2 emissions rather than broader sustainability metrics. This study addresses this gap by empirically examining human capital's influence on ecological footprints in the Indian context through a different theoretical framework.

2.4 Technological progress and environmental quality

The link between technological progress and environmental quality is conceptually promising but empirically nuanced. Recent methodological advances incorporate CO_2 as an undesirable output and energy consumption as a proxy for unobserved pollution, marking a shift toward green TFP (Ahmed and Elfaki, 2024b; Ahmed *et al.*, 2020a). Yet, cross-country comparability and operationalization challenges persist (Elfaki and Ahmed, 2024). Several studies report a negative relationship between innovation as a proxy for technological progress and emissions. Innovation is shown to reduce abatement costs and enhance policy efficiency (Goulder and Schneider, 1999; Buonanno *et al.*, 2003; Popp *et al.*, 2011). Empirical findings by Gerlagh (2007), Grossman and Krueger (1995) and Khalil and Abas (2014) support emission reductions through technological advancement. More recent evidence confirms these trends (Khan *et al.*, 2019; Kahouli, 2018; Ndlovu and Inglesi-Lotz, 2020). In East Asia, nations with strong human capital and ICT infrastructure have achieved productivity-led, low-emission growth (Ahmed, 2012, 2017; Ahmed and Kialashaki, 2023). However, these effects are not universal. Sector-specific differences (Li *et al.*, 2015), varying efficiency levels (Xie *et al.*, 2021) and rebound effects (Acemoglu *et al.*, 2009, 2012; Jaffe *et al.*, 2002) often offset potential gains. Additional complexity arises from renewable energy spillovers and indirect innovation effects (Chen and Lee, 2020; Wang and Zhu, 2020; Jiao *et al.*, 2020). Given the limitations of innovation, R&D and patent rights as proxies for technological progress, the Solow residual offers a broader measure. Despite its potential, environmental research rarely uses TFP. Exceptions include Ahmed and Kialashaki (2023), who link TFP and emissions via the technological Kuznets curve. This study investigates the sustainability character of TFP in India. It bridges the gap by examining how different determinants of TFP contribute to environmental challenges. The analysis explores whether economic efficiency can also translate into environmental efficiency in India.

3. Theoretical foundation, empirical framework and methodology

3.1 Theoretical foundation

Following the research objective to explore the dynamic nexus among ecological footprints, human capital, TFP, HPC and economic growth, this study is grounded in both neo-classical and modern growth theories. It draws theoretical support from the Solow–Swan growth models, endogenous growth theory, the energy-growth hypothesis and the EKC hypothesis. The Harrod–Domar model highlights the role of capital accumulation in driving growth, represented by the equation $G = S/K$ where economic growth depends on the savings rate and capital-output ratio. However, its assumption of fixed coefficients and lack of technological change limit its applicability in long-run analyses. The Solow–Swan model extends this framework by introducing diminishing returns and exogenous technological progress through a Cobb–Douglas production function $Y_t = A_t K_t^{\alpha} L_t^{1-\alpha}$ where TFP, denoted by A_t was assumed exogenously given. When expressed in per capita terms with labor-augmenting technology, the function becomes:$y_t = A_t k_t^{\alpha}$. TFP is estimated as the Solow residual, calculated as: $A_t = \frac{Y_t}{K_t^{\alpha} L_t^{1-\alpha}}$. TFP, estimated as the Solow residual, captures output growth unexplained by capital and labor inputs, reflecting innovation, institutional quality and resource efficiency critical to sustainability (Solow, 1957; Huang *et al.*, 2020). Complementing this is the endogenous growth theory, particularly the contributions of Romer (1990) and Lucas (1988), which emphasize human capital as an internal engine of growth. Human capital not only enhances labor productivity and innovation. Studies have shown that higher levels of education are associated with reduced ecological footprints and greater uptake of renewable energy (Bano *et al.*, 2018; Wang *et al.*, 2018; Barro, 1999; Khan *et al.*, 2025a, 2025b). Regarding the nexus of renewable energy, this study is also grounded in the energy-growth hypothesis, which further strengthens this framework by highlighting the transition from fossil fuels to renewable as a prerequisite for sustainable growth. While fossil fuels have historically powered India's economic expansion, they are a major source of CO_2 emissions. Renewable energy, by contrast, offers a path to decouple growth from environmental degradation. Technological advancement facilitates this transition by improving energy efficiency and reducing carbon intensity (Hasanov *et al.*, 2021). Hydropower, as a key renewable source in India's energy mix, is specifically analyzed to assess its distinct environmental contribution compared to broader renewable aggregate. To evaluate whether India's growth trajectory exhibits sustainability, the study also draws upon the EKC hypothesis, which posits an inverted U-shaped relationship between income and environmental degradation. At low income levels, growth exacerbates environmental damage; beyond a certain threshold, however, increased income supported by investments in human capital, clean energy and innovation leads to environmental improvements (Grossman and Krueger, 1995). Together, these theories provide a multidimensional foundation linking human capital, TFP, HPC and economic growth to environmental outcomes. This integrated theoretical framework, applied to India over the period 1980–1981 to 2022–2023, allows for a systematic examination of whether the country's key growth drivers are aligned with environmental sustainability, providing policy-relevant insights into the green transition process.

3.2 Empirical framework

To achieve the objective of the study, we have taken the ecological footprint as the dependent variable. While CO_2 emissions are the dominant proxy for environmental degradation (Grossman and Krueger, 1995; Kumar and Katoch, 2015; Shahbaz *et al.*, 2016; Wang *et al.*, 2022; Cakar *et al.*, 2021), the ecological footprint offers a broader measure by accounting for pressure on natural resource stocks and bio-capacity (Al-Mulali *et al.*, 2022; Ulucak and Lin, 2017). To capture human capital, we use the human capital index, widely used in environmental modeling (Al-Mulali *et al.*, 2016; Ulucak and Lin, 2017; Ahmed and Wang, 2019a; Danish *et al.*, 2019; Rafindadi and Usman, 2020; Zafar *et al.*, 2019; Chen *et al.*, 2022; Zhang *et al.*, 2021; Abid *et al.*, 2021; Nathaniel *et al.*, 2021; Abbas *et al.*, 2022; Khan *et al.*, 2025a, 2025b, 2025c; Khan *et al.*, 2026). TFP is used as a proxy for technological progress rather than R&D or patent counts, offering a comprehensive measure of efficiency gains (Hall and Jones, 1999; Carlaw and Lipsey, 2003). TFP is estimated using the Solow residual framework following (Oguchi, 2004; van der Eng, 2009; Hasanov *et al.*, 2021; Siddique, 2022; Ahmed and Elfaki, 2024a). HPC is used as a proxy for renewable energy, in line with prior studies (Ali *et al.*, 2019; Tiwari *et al.*, 2022), and is considered the most dominant form of renewable energy in many contexts. We have also used GDP per capita as a proxy for economic growth, and the relationship is hypothesized in line with the EKC (Grossman and Krueger, 1995). The following equation is used for the empirical analysis:

$$EFP_t = f(HC_t, TFP_t, HPC_t, GDP_t, GDPS_t) \tag{1}$$

where

EFP_t represents the ecological footprint, HC_t denotes human capital index; TFP_t represents total factor productivity; HPC_{ts} signifies hydropower consumption, GDP_t measures economic growth; and $GDPS_t$ is the square of economic growth to capture potential nonlinear effects. The empirical form of the model, specified as:

$$EFP_t = \beta_0 + \beta_1 HC_t + \beta_2 TFP_t + \beta_3 HPC_t + \beta_4 GDP_t + \beta_5 GDPS_t + \varepsilon_t \tag{2}$$

where β_0 is the intercept, β_1, β_2, β_3, β_4 and β_5 are coefficients, and ε_t is the error term. Following Shahbaz *et al.* (2012), a log-linear specification is adopted as presented in equation (3):

$$\ln EFP_t = \beta_0 + \beta_1 \ln HC_t + \beta_2 \ln TFP_t + \beta_3 \ln HPC_t + \beta_4 \ln GDP_t + \beta_5 \ln GDPS_t + \varepsilon_t \tag{3}$$

This framework facilitates a robust analysis of the relationships, aligning with established theoretical and empirical approaches in the literature. The data sources and variable description is provided in Table 1.

3.3 Methodology

3.3.1 Unit root test. The augmented Dickey-Fuller (ADF) and Phillips–Perron (PP) unit root tests are used to assess the stationarity properties of time series variables in determining long-run relationships. The ADF test relies on the following equation:

$$\Delta Y_t = \alpha_0 + \alpha_1 Y_{t-1} + \sum_{j-1}^{k} d_j \Delta Y_{tj} + \varepsilon_t \tag{4}$$

In the equation, ε_t represents the pure white noise error term, Δ denotes the difference operator, $Y_t$is a time series, α_0 is the constant and k is the optimum number of lags of the dependent variable. The ADF test checks whether the estimated coefficients are equal to zero. It provides a cumulative distribution of ADF statistics. The variable is said to be stationary if the value of the coefficients δ is less than the critical values from the Fuller table. The equation for the PP unit root test is as follows:

Table 1 Variables description

Variable	*Sign*	*Measurement*	*Data source*
Ecological footprint	EFP_t	Ecological footprint per person	GFN, 2024
Human capital	HC_t	Human capital index	PWT 10.0
Total factor productivity	TFP_t	Using the C–D production function in a Solow framework	Author's estimation
Hydropower consumption	HCP_t	Exajoules	BP, 2021
Economic growth	GDP_t	GDP per capita (constant 2015 US$)	WDI, 2024
Economic growth square	$GDPS_t$	Square of GDP per capita	Author's estimation

Note(s): GFN = global footprint network; WDI = World bank development indicators; BP = British petroleum

$$\Delta Y_t = \alpha + p^* Y_{t-1} + \varepsilon_t \tag{5}$$

The Phillip and Perron unit root test is also based on the *t*-statistics associated with the estimated coefficients ofp^*. One of the shortcomings of the ADF and PP unit root tests remains the negligence of structural breaks identification in the series of data. This negligence of the characteristics of the data can turn into biased results in the estimation of coefficients that may not truly represent the relation. To overcome this shortcoming, we have used the structural breaks unit root test that was developed by Zivot and Andrews (2002). The ZA unit root test determines the time of the structural break, and each series is permitted one structural break. The Zivot–Andrews test considers three models:

$$\boldsymbol{Model}\quad \boldsymbol{A}: \Delta yt = \mu + \alpha y_{t-1} + \gamma DUt + \sum_{j=1}^{k} \delta_j \Delta y_{t-1} + \varepsilon_t \tag{6}$$

$$\boldsymbol{Model}\quad \boldsymbol{B}: \Delta yt = \mu + \alpha y_{t-1} + \theta DTt + \sum_{j=1}^{k} \delta_j \Delta y_{t-1} + \varepsilon_t \tag{7}$$

$$\boldsymbol{Model}\quad \boldsymbol{C}: \Delta yt = \mu + \alpha y_{t-1} + \gamma DUt + \theta DTt + \sum_{j=1}^{k} \delta_j \Delta y_{t-1} + \varepsilon_t \tag{8}$$

where:

DUt $=\begin{cases} 1 if \;\; t > TB, \\ 0, \;\; otherwise, \end{cases}$ captures a one-time change in the intercept, otherwise;

DUt $=\begin{cases} t - TB, \;\; if \;\; t > TB \\ 0, \;\; otherwise, \end{cases}$ captures a one-time change in the intercept, otherwise;

TB is the break year determined endogenously by the model; and

ε_t is a white-noise error term.

3.3.2 Autoregressive distributed lag bound testing approach. To investigate the long-run and short-run dynamics between the variables, we choose the ARDL bounds testing approach developed by Pesaran and Pesaran (1997), Pesaran and Shin (1999) and Pesaran *et al.* (2000, 2001) instead of other conventional techniques. The ARDL approach has many advantages over other co-integration methods. ARDL may be applied irrespective of whether the underlying variables are purely I(0), I(1) or mutually co-integrated (Pesaran and Shin, 1999). The ARDL approach has better small-sample properties (Huang, 2002). In the ARDL procedure, the estimation of results is possible even if the explanatory variables are endogenous. The empirical ARDL equation is formulated as follows:

$$\begin{aligned} \Delta EFP_t = {} & \beta_0 + \beta_{1k}\sum_{k=1}^{n}\Delta EFP_{(t-k)} + \beta_{2k}\sum_{k=1}^{n}\Delta HC_{(t-k)} + \beta_{3k}\sum_{k=1}^{n}\Delta TFP_{(t-k)} + \beta_{4k}\sum_{k=1}^{n}\Delta HPC_{(t-k)} \\ & + \beta_{5k}\sum_{k=1}^{n}\Delta GDP_{(t-k)} + \beta_{6k}\sum_{k=1}^{n}\Delta \mathrm{GDPS}_{(t-k)} + \lambda_1 EFP_{(t-1)} + \lambda_2 HC_{(t-1)} + \lambda_3 TFP_{(t-1)} \\ & + \lambda_4 HPC_{(t-1)} + \lambda_5 GDP_{(t-1)} + \lambda_6 GDPS_{(t-1)} + \varepsilon_{1t} \end{aligned} \tag{9}$$

$$\begin{aligned} \Delta HC_t = {} & \beta_0 + \beta_{1k}\sum_{k=1}^{n}\Delta HC_{t-k} + \beta_{2k}\sum_{k=1}^{n}\Delta EFP_{(t-k)} + \beta_{3k}\sum_{k=1}^{n}\Delta TFP_{(t-k)} + \beta_{4k}\sum_{k=1}^{n}\Delta \mathrm{HPC}_{(t-k)} \\ & + \beta_{5k}\sum_{k=1}^{n}\Delta GDP_{(t-k)} + \beta_{6k}\sum_{k=1}^{n}\Delta GDPS_{(t-k)} + \lambda_1 HC_{(t-1)} + \lambda_2 EFP_{(t-1)} \\ & + \lambda_3 TFP_{(t-1)} + \lambda_4 HPC_{(t-1)} + \lambda_5 GDP_{(t-1)} + \lambda_6 GDPS_{(t-1)} + \varepsilon_{2t} \end{aligned} \tag{10}$$

$$\Delta TFPt = \beta_0 + \beta_{1k}\sum_{k=1}^{n}\Delta \mathrm{TFP}_{t-k} + \beta_{2k}\sum_{k=1}^{n}\Delta \mathrm{EFP}_{(t-k)} + \beta_{3k}\sum_{k=1}^{n}\Delta HC_{(t-k)} + \beta_{4k}\sum_{k=1}^{n}\Delta HPC_{(t-k)}$$
$$+ \beta_{5k}\sum_{k=1}^{n}\Delta GDP_{(t-k)} + \beta_{6k}\sum_{k=1}^{n}\Delta GDPS_{(t-k)} + \lambda_1 \mathrm{TFP}_{(t-1)} + \lambda_2 \mathrm{EFP}_{(t-1)}$$
$$+ \lambda_3 HC_{(t-1)} + \lambda_4 HPC_{(t-1)} + \lambda_5 GDP_{(t-1)} + \lambda_6 GDPS_{(t-1)} + \varepsilon_{3t} \quad (11)$$

$$\Delta HPC_t = \beta_0 + \beta_{1k}\sum_{k=1}^{n}\Delta \mathrm{HPC}_{(t-k)} + \beta_{2k}\sum_{k=1}^{n}\Delta \mathrm{EFP}_{(t-k)} + \beta_{3k}\sum_{k=1}^{n}\Delta HC_{(t-k)} + \beta_{4k}\sum_{k=1}^{n}\Delta TFP_{(t-k)}$$
$$+ \beta_{5k}\sum_{k=1}^{n}\Delta \mathrm{GDP}_{(t-k)} + \beta_{6k}\sum_{k=1}^{n}\Delta GDPS_{(t-k)} + \lambda_1 HPC_{(t-1)} + \lambda_2 EFP_{(t-1)} + \lambda_3 \mathrm{HC}_{(t-1)}$$
$$+ \lambda_4 TFP_{(t-1)} + \lambda_5 GDP_{(t-1)} + \lambda_6 \mathrm{GDPS}_{(t-1)} + \varepsilon_{4t} \quad (12)$$

$$\Delta GDP_t = \beta_0 + \beta_{1k}\sum_{k=1}^{n}\Delta \mathrm{GDP}_{(t-k)} + \beta_{2k}\sum_{k=1}^{n}\Delta \mathrm{EFP}_{(t-k)} + \beta_{2k}\sum_{k=1}^{n}\Delta HC_{(t-k)} + \beta_{3k}\sum_{k=1}^{n}\Delta TFP_{(t-k)}$$
$$+ \beta_{4k}\sum_{k=1}^{n}\Delta \mathrm{HPC}_{(t-k)} + \beta_{5k}\sum_{k=1}^{n}\Delta GDPS_{(t-k)} + \lambda_1 GDP_{(t-1)} + \lambda_2 EFP_{(t-1)} + \lambda_3 HC_{(t-1)}$$
$$+ \lambda_4 \mathrm{TFP}_{(t-1)} + \lambda_5 HPC_{(t-1)} + \lambda_6 GDPS_{(t-1)} + \varepsilon_{5t} \quad (13)$$

$$\Delta GDPS_t = \beta_0 + \beta_{1k}\sum_{k=1}^{n}\Delta \mathrm{GDPS}_{(t-k)} + \beta_{2k}\sum_{k=1}^{n}\Delta \mathrm{EFP}_{(t-k)} + \beta_{3k}\sum_{k=1}^{n}\Delta HC_{(t-k)} + \beta_{4k}\sum_{k=1}^{n}\Delta TFP_{(t-k)}$$
$$+ \beta_{5k}\sum_{k=1}^{n}\Delta \mathrm{HPC}_{(t-k)} ++ \beta_{6k}\sum_{k=1}^{n}\Delta \mathrm{GDP}_{t-k} + \lambda_1 GDPS_{(t-1)} + \lambda_2 EFP_{(t-1)} + \lambda_3 HC_{(t-1)}$$
$$+ \lambda_4 \mathrm{TFP}_{(t-1)} + \lambda_5 HPC_{(t-1)} + \lambda_6 GDP_{(t-1)} + \varepsilon_{6t} \quad (14)$$

where Δ indicates the first difference, $\beta_o$is a constant, $\varepsilon$is the residual, β_1, β_2 ,β_3 ,β_4 ,β_5 & β_6 are the short-run coefficients, while $\lambda_1, \lambda_2, \lambda_3, \lambda_4$,λ_5 & λ_6 are the long-run coefficients. We estimate the long-run relationship between the variables by testing the null hypothesis of no co-integration $H_O = \lambda_{1=}\lambda_{2=}\lambda_{3=}\lambda_{4=}\lambda_5 = \lambda_6 = 0$ against the alternative hypothesis $H_1 = \lambda_1 \neq \lambda_2 \neq \lambda_3 \neq \lambda_4 \neq \lambda_5 \neq \lambda_6 \neq 0$. *F*-statistic value is used to determine the co-integration. The critical values given by Pesaran *et al.* (2001) show whether to accept or reject the null hypothesis. If the *F*-statistic values lie within the critical values, the result will be inconclusive, while in case the *F*-statistic lies above the critical values, the result will be considered conclusive; however, lower than the critical value means no co-integration. This study used the Akaike information criteria (AIC) for lag length selection. If the long-run relationship between relationship ecological footprints, human capital, TFP, HPC, economic growth and growth square exists, then we estimate the long-run coefficients. The following empirical equation will be used to estimate the long-run coefficients:

$$\Delta EFP_t = \delta_0 + \delta_1\sum_{i=1}^{0} EFP_{(t-1)} + \delta_2\sum_{i=1}^{0} HC_{(t-1)} + \delta_3\sum_{i=1}^{0} TFP_{(t-1)} + \delta_4\sum_{i=1}^{0} HPC_{(t-1)}$$
$$+ \delta_5\sum_{i=1}^{0} GDP_{(t-1)} + \delta_6\sum_{i=1}^{0} GDPS_{(t-1)} + \mu_t \quad (15)$$

If this study finds evidence of long-run relationship between ecological footprints, human capital, TFP, HPC, economic growth and growth square, then to estimate the short-run coefficients, the following empirical equation will be used:

$$\Delta EFP_t = \phi_0 + \phi_1\sum_{i=1}^{0}\Delta EFP_{t-1} + \phi_2\sum_{i=1}^{0}\Delta HC_{t-1} + \phi_3\sum_{i=1}^{0}\Delta TFP_{t-1} + \phi_4\sum_{i=1}^{0}\Delta HPC_{t-1}$$
$$+ \phi_5\sum_{i=1}^{0}\Delta GDP_{t-1} + \phi_5\sum_{i=1}^{0}\Delta GDPS_{t-1} + nEC_{t-1} + \mu_t \quad (16)$$

The error correction term (nEC_{t-1}) shows the speed of adjustment needed to restore the long-run equilibrium following a short-run shock. The n is the coefficient of the error correction term in the equation that indicates the speed of adjustments.

3.3.3 Vector error correction model Granger causality. The ARDL bounds testing approach is an ideal method to investigate co-integration among the variables; however, it lacks the ability to provide the direction of causality. Hence, the Granger causality technique is used to determine the direction of causality among the variables. Granger causality indicates the direction of influence and identifies which variable causes another (Granger, 1988). A negative and significant coefficient of the ECM indicates a long-run relationship, while short-run causality can be confirmed from the F-value of the Wald statistics. The VECM framework for this study is constructed as follows:

$$\begin{bmatrix} \Delta lnEFP_t \\ \Delta lnHC_t \\ \Delta ln\mathrm{TFP}_t \\ \Delta lnHPC_t \\ \Delta lnGDP_t \\ \Delta lnGDPS_t \end{bmatrix} = \begin{bmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \\ \beta_4 \\ \beta_5 \\ \beta_6 \end{bmatrix} = \begin{bmatrix} \beta_{11,k}\beta_{12,k}\beta_{13,k}\beta_{14,k}\beta_{15,k} \\ \beta_{21,k}\beta_{22,k}\beta_{23,k}\beta_{24,k}\beta_{25,k} \\ \beta_{31,k}\beta_{32,k}\beta_{33,k}\beta_{34,k}\beta_{35,k} \\ \beta_{41,k}\beta_{42,k}\beta_{43,k}\beta_{44,k}\beta_{45,k} \\ \beta_{51,k}\beta_{52,k}\beta_{53,k}\beta_{54,k}\beta_{55,k} \\ \beta_{61,k}\beta_{62,k}\beta_{63,k}\beta_{64,k}\beta_{65,k} \end{bmatrix} \times \begin{bmatrix} \Delta lnEFP_{t-1} \\ \Delta lnHC_{t-1} \\ \Delta ln\mathrm{TFP}_{t-1} \\ \Delta lnHPC_{t-1} \\ \Delta lnGDP_{t-1} \\ \Delta lnGDPS_{t-1} \end{bmatrix} + \ldots$$

$$+ \begin{bmatrix} \beta_{11,m}\beta_{12,m}\beta_{13,m}\beta_{14,m}\beta_{15,m} \\ \beta_{21,m}\beta_{22,m}\beta_{23,m}\beta_{24,m}\beta_{25,m} \\ \beta_{31,m}\beta_{32,m}\beta_{33,m}\beta_{34,m}\beta_{35,m} \\ \beta_{41,m}\beta_{42,m}\beta_{43,m}\beta_{44,m}\beta_{45,m} \\ \beta_{51,m}\beta_{52,m}\beta_{53,m}\beta_{54,m}\beta_{55,m} \\ \beta_{61,m}\beta_{62,m}\beta_{63,m}\beta_{64,m}\beta_{65,m} \end{bmatrix} \times \begin{bmatrix} \Delta lnEFP_{it} \\ \Delta lnHC_{it} \\ \Delta ln\mathrm{TFP}_{it} \\ \Delta lnHPC_{it} \\ \Delta lnGDP_{it} \\ \Delta lnGDPS_{it} \end{bmatrix} + \begin{bmatrix} n_1 \\ n_2 \\ n_3 \\ n_4 \\ n_5 \\ n_6 \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \\ \varepsilon_{4t} \\ \varepsilon_{5t} \\ \varepsilon_{6t} \end{bmatrix} \times (ecm_{t-1}) + \begin{bmatrix} \mu_{1t} \\ \mu_{2t} \\ \mu_{3t} \\ \mu 4_t \\ \mu_{5t} \\ \mu_{6t} \end{bmatrix}$$

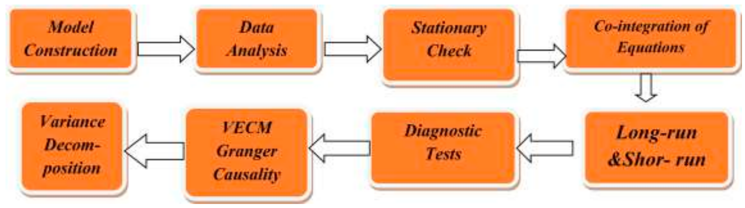
where Δ is the difference operator and ecm_{t-1} is the lagged error correction term, generated from the long-run association. The long-run causality is found by the significance of the coefficient of the lagged error correction term using t-test statistic. The existence of a significant relationship in the first difference of the variables provides evidence on the direction of short-run causality. The joint X^2 statistic for the first differenced lagged independent variables is used to test the direction of the short-run causality between the variables, where t stands for the time period, $t-1$ stands for the lagged values of the time period and ε stands for the residual term. Furthermore, AIC is selected as the lag length criteria for this study. Variance decomposition methods have been used to examine the robustness of the causal relationship between human capital, economic growth and environmental outcomes. Graphical representation of research design and methodology is provided in Figure 2.

4. Results and discussion

4.1 Preliminary analysis

Based on the descriptive statistics presented in Table 2, the ecological footprint (EFP) in India during the study period has an average value of −0.0976, ranging between −0.2405 and 0.0346, indicating environmental pressure, with the lowest standard deviation (0.0857), suggesting high stability around its mean. HC shows a mean of 0.2435, ranging from 0.1072 to 0.3560, reflecting steady educational improvements. TFP averages 0.8091, with a standard deviation of 0.1199, suggesting moderate consistency. HPC averages 1.9468,

Figure 2 Research design and methodological framework



Source: Authors' own work

Table 2 Descriptive statistics

Statistic	lnEFP	lnHC	lnTFP	lnHPC	lnGDP	lnGDPS
Mean	−0.0976	0.2435	0.8091	1.9468	2.9347	8.6662
Median	−0.1094	0.2636	0.7787	1.9096	2.8954	8.3835
Maximum	0.0346	0.3560	1.0277	2.2428	3.3495	11.2193
Minimum	−0.2405	0.1072	0.6578	1.6816	2.5956	6.7376
Std. dev.	0.0857	0.0764	0.1199	0.1703	0.2339	1.3863
Skewness	0.0926	−0.2845	0.5948	0.0981	0.2327	0.3120
Kurtosis	1.7097	1.7505	2.1124	1.7074	1.7317	1.7743
Jarque–Bera	3.1152	3.4560	4.0389	3.1334	3.3461	3.4677
Probability	0.2106	0.1776	0.1327	0.2087	0.1876	0.1766
Sum	−4.2955	10.7174	35.6020	85.6626	129.1289	381.3136
Sum sq. dev.	0.3164	0.2516	0.6188	1.2472	2.3531	82.6471
Observations	44	44	44	44	44	44

Source(s): Author's estimation using data from World Development Indicators and Penn World Table 10

with a range from 1.6816 to 2.2428, also indicating consistent growth. Economic growth (GDP) maintains a mean of 2.9347, with values between 2.5956 and 3.3495, likely reflecting reform-led expansion. The squared economic growth (GDPS), representing economic intensity, has a higher mean of 8.6662 and the widest range, from 6.7376 to 11.2193, with the highest standard deviation of 1.3863, indicating significant variability. All variables exhibit low skewness and platykurtic distributions, with Jarque–Bera test probabilities confirming no significant departure from normality.

4.2 Stationary check

Based on the results presented in Table 3, all variables become stationary after first differencing, as confirmed by the ADF and PP tests. The results indicate that ecological footprint, human capital, TFP, HPC and economic growth indicators are integrated of order one, I(1), suggesting that the order of integration does not exceed one (i.e. $p \leq 1$). The Zivot–Andrews test further confirms the stationarity of all variables at the level or first difference, identifying structural breaks primarily between 1988 and 1994, as shown in Table 3. These breakpoints align with India's economic liberalization phase, reflecting structural shifts in the data (Ahluwalia, 2002; Panagariya, 2008). Overall, all variables exhibit an order of integration of either I(0) or I(1), with none integrated of order two, I(2). The presence of such breaks highlights the importance of accounting for structural dynamics and justifies the use of the ARDL bounds testing approach, which accommodates both I(0) and I(1) variables in long-run analysis.

Table 3 Stationarity tests

Variable	*ADF Level*	Δ	*PP Level*	Δ	*ZA Level*	*Break-date*	Δ	*Break-date*
lnEFP	−3.250	−6.090*	−2.564	−6.067*	−6.41	1994	−9.857*	1991
lnHC	−2.059	−5.503*	−4.685	−6.89*	−5.65	1991	−5.96***	1990
lnTFP	−6.721***	−3.453*	−1.435***	−2.432*	−5.69	1988	−6.73**	1994
lnHPC	−1.758***	−1.298*	−5.390***	−4.124*	−5.89	1982	−8.857*	1989
lnGDP	−2.266	−9.309*	−4.230	−1.034*	−6.36	1990	−5.122**	1991
lnGDPS	−4.778*	−3.909*	−3.670*	−3.289*	−5.74	1992	−9.857*	1988

Note(s): *, ** and *** denote significance at 1, 5 and 10% levels. Δ = first difference. ADF, PP and ZA tests confirm I(0)/I(1) integration [no I(2)], supporting ARDL; ZA allows one structural break
Source(s): Authors' estimation

4.3 Co-integration analysis

In the ARDL estimation framework, the initial step involves selecting the optimal lag length using a vector autoregression model (Ganai *et al.*, 2025). Based on standard criteria and the AIC, a lag length of one was identified as optimal. To evaluate the existence of long-run equilibrium relationships among the variables, the ARDL bounds testing approach, as proposed by Pesaran *et al.* (2001), was used. As presented in Table 4, the computed *F*-statistics for all six models exceed the 5% upper bound critical value, leading to the rejection of the null hypothesis of no co-integration. Specifically, the *F*-statistics are 6.03 for the ecological footprint equation, 7.31 for the human capital equation, 9.90 for the TFP equation, 9.73 for the HPC equation, 8.21 for the economic growth equation and 4.10 for the squared term of the economic growth equation. These values, all above the 5% significance threshold, provide robust evidence of long-run co-integrating relationships among the study variables in the Indian context. The confirmation of co-integration validates the use of ARDL-based long-run estimation techniques and further supports the implementation of VECM to capture short-run adjustments and assess the direction of causality through Wald tests. This comprehensive econometric strategy allows for an in-depth and dynamic analysis of the interlinkages among ecological footprints, human capital, TFP, HPC and economic growth in India.

4.4 Model estimation and interpretation

Following the confirmation of co-integration, equations (15) and (16) were used to assess the long- and short-run impacts of human capital, TFP, HPC, economic growth and its squared term on ecological footprint in India. As shown in Table 5, human capital emerges as a significant key determinant in reducing ecological footprints in India, with a 1% rise in

Table 4 Co-integration Table 06 (A–F): results of ARDL bound test

Estimated model	N	*Lag order (dependent and regressors)*	*Co-integration*
lnEFP/lnHC, lnTFP, lnHPC, lnGDP and lnGDPS	6.03**	(1, 2, 2, 2, 1, 2)	Yes
lnHC/lnEFP, lnTFP, lnHPC, lnGDP and lnGDPS	7.31**	(1, 2, 1, 2, 1, 2)	Yes
lnTFP/lnEFP, lnHC, lnHPC, lnGDP and lnGDPS	9.90*	(1, 2, 2, 1, 1, 2)	Yes
lnHPC/lnEFP, lnHC, lnTFP, lnGDP and lnGDPS	9.73*	(1, 1, 2, 2, 1, 2)	Yes
lnGDP/lnEFP, lnHC, lnTFP, lnHPC and lnGDPS	8.21*	(1, 1, 2, 2, 1, 2)	Yes
lnGDPS/lnEFP, lnHC, lnTFP, lnHPC and lnGDP	4.10**	(1, 2, 1, 2, 1, 2)	Yes

Note(s): *F*-statistics: lnTFP (9.90), lnHPC (9.73) and lnGDP (8.21) > 1% upper bound (5.326) → Cointegration at 1% level. lnEFP (6.03), lnHC (7.31) and lnGDPS (4.10) > 5% upper bound (3.960), but < 1% → Cointegration at 5% level; ** denotes significance at 5% level and * denotes 1% of siginificance levels
Source(s): Authors' estimation

Table 5 Long-run, short-run and diagnostic test results

Variable/test	*Co-efficient*	t-*statistic*	*Prob.*
Long-run results			
lnHC	–2.1183**	–2.3570	0.0243
lnTFP	0.0474*	0.1382	0.0190
lnHPC	0.1041**	0.7873	0.0435
lnGDP	5.7727**	2.4014	0.0219
lnGDPS	–0.8174**	–2.1490	0.0388
Short-run results (Δ)			
ΔlnEFP(−1)	0.7444*	7.0662	0.0000
ΔlnHC	–0.5413**	–2.7545	0.0094
ΔlnTFP	0.2108***	1.8242	0.0706
ΔlnHPC	0.0266**	0.9039	0.0372
ΔlnGDP	1.4752**	2.4427	0.0199
ΔlnGDPS	–0.0838**	–0.8563	0.0393
ECT	–0.2555*	–6.2200	0.0000
Diagnostic tests			
Breusch–Godfrey serial correlation	0.6415	–	0.5370
Normality (Jarque–Bera)	23.1881	–	0.7023
Ramsey RESET test	0.0576	–	0.8127
Breusch–Pagan–Godfrey heteroskedasticity	1.3586	–	0.2524

Note(s): *, ** and *** denote significance at 1, 5 and 10% levels, respectively ($p < 0.01$, $p < 0.05$ and $p < 0.10$). Δ denotes first-difference (short-run) variables. Estimations are based on the ARDL model with structural break dummies
Source(s): Authors' estimation

human capital reducing ecological footprints by 2.118% in the long run and 0.541% in the short run, indicating both enduring and immediate environmental gains. Three core mechanisms underpin this negative relationship. First, the scale effect suggests that improved human capital drives economic growth, which, beyond a certain threshold, facilitates environmental improvement (Haldar and Mallik, 2010; Ghatak and Jha, 2012; Khan *et al.*, 2022; Ahmed and Wang, 2019; Bano *et al.*, 2018). Second, the technique and composition effects highlight that better-educated populations foster cleaner technologies and shift economic structure away from resource-intensive sectors toward knowledge-based services (Miller and Upadhyay, 2000; Ahmed *et al.*, 2020b). Third, the awareness effect captures how increased education enhances environmental consciousness, encouraging sustainable behaviors and consumption choices (Becker, 2002; Singh, 2024). These mechanisms are validated by findings from various regional contexts, including Europe, China and India (Marques and Fuinhas, 2011; Zafar *et al.*, 2019; Yao *et al.*, 2021; Khan *et al.*, 2025a, 2025b).

However, the present study contrasts with studies such as Lan and Munro (2013), Chankrajang and Muttarak (2017), Cakar *et al.* (2021), Zhang *et al.* (2021) and Du *et al.* (2022), which report contradictory evidence. Hazwan (2021) argues that the positive environmental effects of human capital in India are constrained by weak institutional frameworks, while Dong *et al.* (2022) suggest that in developing nations, human capital can intensify ecological degradation through industrial expansion. Regional disparities in India's educational infrastructure, particularly between urban and rural areas, further restrict the environmental gains associated with human capital formation, as urban-focused policies tend to overlook peripheral regions.

Another important finding of the study is that TFP, serving as a proxy for technological progress, has a modest yet statistically significant positive impact on the ecological footprint in India. Results presented in Table 5 indicate that a 1% increase in TFP is associated with a 0.0474% rise in the ecological footprint in the long run and a 0.2108% rise in the short run. These findings suggest that it is economic efficiency, rather than environmental concern, that TFP supports. These findings support studies highlighting adverse environmental impacts of TFP in weak regulatory settings (Khan *et al.*, 2019; Kahouli, 2018; Ndlovu and Inglesi-Lotz, 2020). However, these findings contrast with global evidence suggesting that TFP can reduce environmental pressure (Gerlagh, 2007; Grossman and Krueger, 1995; Khalil and Abas, 2014). The divergence likely stems from India's uneven technological development, where TFP gains are concentrated in capital-intensive sectors with limited spillover to the informal, resource-intensive economy (Hasan, 2002). While R&D enhances productivity and employment (Hasan, 2002; Mitra and Jha, 2016), it may also induce environmental strain through automation (Nica, 2016). In the Indian economy, post-1991 growth increasingly relied on TFP and capital accumulation (Das *et al.*, 2021), driven by rising FDI and service sector expansion (Ghosh, 2010), but lacked corresponding reforms in environmental governance. Weak infrastructure, limited diffusion of green technologies and poor regulatory enforcement have restricted the environmental benefits of TFP. Globally, TFP is driven by R&D (Hall, 2011; Coe *et al.*, 2009), trade and global value chain integration (De Loecker, 2013; Alcalá and Ciccone, 2004), FDI-led technology diffusion, efficient resource allocation (Hsieh and Klenow, 2009) and institutional quality (Isaksson, 2007). In India, however, this study concludes that these drivers have often fueled energy- and resource-intensive growth without adequate environmental protections. As such, while TFP has contributed to economic efficiency, it has also amplified the ecological footprint, highlighting the urgent need for policy frameworks that align productivity gains with environmental sustainability.

One of the important findings of the study is that HPC significantly increases the ecological footprint, thereby posing a substantial challenge to India's renewable energy transition. Empirical evidence, as presented in Table 5, indicates that a 1% increase in HPC leads to a 0.104% rise in the ecological footprint in the long run and a 0.0266% increase in the short run. These results highlight the environmental trade-offs associated with HPC. The findings are consistent with Al-Mulali *et al.* (2016), who documented increased water and land footprints from renewable electricity generation in a panel of 59 countries. Further support is drawn from Shakya and Shrestha (2011), Li *et al.* (2020) and Zhang *et al.* (2015), who reported notable GHG emissions from hydropower reservoirs, highlighting the environmental costs of such projects. However, the present results contrast with studies such as Solarin *et al.* (2017), which identified a long-run negative association between hydroelectricity and CO_2 emissions in China and India. Similarly, Adebayo *et al.* (2023) and Bello *et al.* (2018) found that hydropower reduces the ecological footprint and CO_2 emissions over time, pointing to the context-specific nature of hydropower's environmental impact. Additionally, Ummalla and Samal (2018) found no significant influence of hydropower on CO_2 emissions in the case of China, further emphasizing variability in outcomes across regions. One plausible explanation for the observed increase in the ecological footprint from HPC in India lies in the rising electricity demand driven by its vast and growing population – the second-largest globally. This is consistent with global trends, as the ecological deficit has widened significantly since 1970 due to population pressures and escalating resource demand (Pandey *et al.*, 2020). Another contributing factor may be the geographical concentration of large-scale hydropower projects in ecologically sensitive regions such as the Himalayas, which has led to biodiversity loss and the displacement of local communities, undermining the sustainability of such energy solutions (Kaunda *et al.*, 2012; Sternberg, 2008). Even small hydropower projects in India, though often considered efficient and low-carbon, have been criticized for inadequate planning and monitoring, resulting in stream depletion, hill tunneling and irreversible socio-environmental impacts (Kumar and Katoch, 2015). Furthermore, environmental concerns related to hydropower infrastructure include water losses (Gleick, 1993) and ecosystem disturbances, such as alterations in air temperature and water quality (Rajwa-Kuligiewicz *et al.*, 2015; Abell, 1994). Alsaleh and Abdul-Rahim (2021) also noted that hydropower plants can degrade surrounding environments by emitting pollutants and disrupting soil and habitat integrity – effects that appear increasingly relevant in the context of India's current hydropower development trajectory.

The findings of this study further reveal that economic growth has a statistically significant and positive impact on the ecological footprint in India, highlighting the enduring trade-off between growth and environmental sustainability. Specifically, a 1% increase in economic growth leads to a 5.7727% rise in the ecological footprint in the long run and a 1.4752% rise in the short run, as shown in Table 5. These results emphasize the environmental burden of India's resource-intensive growth pattern, driven by industrialization, urbanization and increasing consumption. However, the negative and statistically significant coefficients of the squared economic growth term lend support to the EKC hypothesis. According to the results, a 1% increase in the square of economic growth reduces the ecological footprint by 0.8174% in the long run and by 0.0838% in the short run. This suggests that as income levels rise, environmental quality tends to improve due to the adoption of cleaner technologies, stronger regulations and more effective environmental governance. The positive coefficient on economic growth and the negative coefficient on its squared term confirm the existence of an inverted U-shaped EKC in the Indian context. This finding aligns with a substantial body of empirical literature supporting the EKC hypothesis across various national and regional contexts, including Rafindadi and Usman (2020), Danish *et al.* (2019), Zafar *et al.* (2019), Dasgupta *et al.* (2002), Shiraz *et al.* (2021), Odugbesan and Adebayo (2020), Sinha and Bhattacharya (2017), Ozgur *et al.* (2022) and Jayanthakumaran *et al.* (2010). A plausible explanation lies in India's historical development focus, which has prioritized poverty reduction and employment over environmental sustainability. This has resulted in deforestation, pollution and over-extraction of natural resources. The relatively stronger long-run impact reflects deep-rooted ecological stress, whereas the more moderate short-run effect indicates less persistent but immediate environmental consequences. India's reliance on fossil fuels – particularly coal – and historically weak environmental regulation during the early liberalization period have further exacerbated ecological degradation. Conversely, the findings contradict those of Ghosh (2010) and Jena *et al.* (2022), who found no long-run causal link between economic growth and environmental degradation in India. The coefficient of the error correction term (ECT = −0.2555) is negative and statistically significant, confirming the existence of a long-run equilibrium relationship among the variables. The value of −0.2555 indicates that approximately 25.55% of the disequilibrium from the previous period is corrected in the current period. In other words, the system converges to its long-run equilibrium at a moderate speed of adjustment each period. The diagnostic test results presented in Table 5 confirm the statistical robustness of the ARDL model, indicating that key classical assumptions are upheld. The absence of serial correlation, normality of residuals, correct model specification and homoscedastic variance collectively validate the model's reliability. These findings enhance the credibility of the estimated short-run and long-run coefficients, ensuring sound empirical inference and robust policy implications.

4.5 Vector error correction model-based Granger causality approach

To examine the direction and nature of causality among the variables, we employed the VECM-based Granger causality approach, which allows for distinguishing between short-run dynamics and long-run equilibrium relationships in the presence of co-integrated variables. This method uses Wald tests for short-run causality, the significance of the ECT for long-run causality and combined joint tests for overall causal interactions. The results reported in Table 6 indicate that human capital, TFP, HPC, economic growth and its square all exhibit unidirectional short-run causality toward the ecological footprint, with no evidence of reverse causality, as presented in Table 6. This absence of feedback effects highlights the asymmetry in India's economic growth–environment nexus. While structural and

Table 6 VECM Granger causality results

Dependent variable	Short-run causality (χ^2, p-value)	Long-run causality (ECT_{t-1}, p-value)	Joint long-run and short-run causality (χ^2, p-value)
ΔEFP_t	HC (32.19, 0.001) TFP (21.32, 0.002) HPC (16.35, 0.001) GDP (62.10, 0.009) GDPS (8.92, 0.0003)	–0.13 (0.001)	16.18 (0.000) HC: 9.12 (0.023) TFP: 32.21 (0.034) GDP: 21.23 (0.005)
ΔHC_t	EFP (9.06, 0.22) TFP (9.12, 0.98) HPC (3.23, 0.88) GDP (37.2, 0.98)	Not significant	Not significant
ΔTFP_t	EFP (8.98, 0.36) HC (7.21, 0.009) GDP (6.99, 0.03) GDPS (51.9, 0.950)	0.65 (0.004)	Significant joint causality with GDPS
ΔHPC_t	EFP (9.06, 0.48) HC (1.48, 0.23) GDPS (9.89, 0.98)	Not reported	Not reported
ΔGDP_t	EFP (3.78, 0.43) HC (8.34, 0.04) TFP (21.32, 0.004) HPC (0.51, 0.07)	–0.65 (0.003)	Significant joint causality
$\Delta GDPS_t$	EFP (21.09, 0.89) HPC (1.09, 0.003)	Not reported	Not reported

Note(s): Values in parentheses are *p*-values. Short-run causality is tested via the Wald χ^2 test; long-run causality via the significance of the error correction term (ECT); and joint effects via combined tests
Source(s): Authors' estimation

macroeconomic variables drive environmental degradation, environmental degradation does not yet visibly influence these drivers. The significant and negative ECT for the ecological footprint equation confirms long-run adjustment, indicating that the environmental consequences of growth are not transient but structurally embedded. Human capital Granger-causes the ecological footprint, economic growth and TFP in a unidirectional manner. The unidirectional Granger causality from human capital to the ecological footprint indicates that, as human capital improves, it introduces a sustainability dimension to growth by enhancing output, altering its composition and increasing awareness. This establishes human capital as an exogenous, policy-driven input. Human capital Granger-causes economic growth and is also the only variable showing significant long-run causality in the TFP equation, suggesting that skill formation and educational development are essential for enhancing productivity in India. This dynamic aligns with endogenous growth theory, particularly the Romer–Lucas framework, where human capital is the key driver of technological progress and innovation. TFP, representing technological efficiency, also Granger-causes both the ecological footprint and economic growth in the long run, but its effect is environmentally detrimental, implying that productivity gains are currently resource-intensive and not yet green. The results align with the view that India's technological progress, while advancing output, is not decoupled from environmental degradation – likely due to limited diffusion of clean technologies and institutional constraints. HPC exhibits short-run causality to the ecological footprint, confirming the results of a positive association in the case of India, but the absence of significant long-run or joint causality suggests a limited structural role of HPC in India's energy mix. Furthermore, no significant causal flows from economic growth to HPC indicate that energy transitions have not been effectively integrated into growth. However, no significant causality is found from economic growth or human capital to HPC, reflecting weak linkages between human development, output expansion and the clean energy transition. Economic growth and its square exhibit unidirectional causality toward the ecological footprint in both time horizons. The short-run relationship reflects growth-led environmental degradation, while the squared term supports the EKC hypothesis, indicating that beyond a certain income level, growth contributes to environmental improvement. The negative and statistically significant ECT for the ecological footprint confirms long-run equilibrium reversion. Economic growth is jointly influenced by human capital and TFP, positioning it as a central variable in the growth–environment nexus. The empirical findings presented in Table 6 also indicate that the ecological footprint emerges as the most responsive variable in the system, influenced by all study variables in the short run. Yet, the absence of reverse causality highlights that environmental degradation has not yet imposed a binding constraint on macroeconomic performance or policy recalibration, an outcome characteristic of many emerging economies in transitional phases of development. Overall, these results emphasize the centrality of human capital and TFP in shaping both economic outcomes and environmental trajectories in India and their directional aspect is presented in Table 7.

4.6 *Variance decomposition*

The generalized forecast error variance decomposition results in Table 8 offer key insights into the evolving drivers of the ecological footprint over a ten-period horizon within a vector autoregressive framework. Initially, fluctuations in the ecological footprint are entirely self-driven. By period two, own shocks decline to 85.43%, with economic growth (5.12%), human capital (4.57%), HPC (2.35%), TFP (1.54%) and squared economic growth (0.98%) beginning to exert influence. As the system evolves, external factors become more prominent. By period five, own shocks drop to 31.05%, while HPC (24.01%), economic growth (19.88%) and human capital (13.80%) emerge as leading contributors. TFP rises to 9.28%, while the squared growth term remains marginal at 1.88%. By the tenth period, only 19.11% of the ecological footprint variance is due to own shocks. Economic growth leads at 27.18%, followed by HPC (23.57%), TFP (14.00%) and human capital (12.35%). The squared growth term remains the least influential at 3.79%. The variance decomposition of the ecological footprint is represented graphically in Figure 3. Additionally, graphical representations play a crucial role in visualizing trends and results. The included graphs illustrate the model equations used to derive the

Table 7 Granger causality results (based on VECM estimates)

Causality direction	*Short-run causality*	*Long-run causality*
HC → EF	Yes (unidirectional)	Yes (unidirectional)
TFP → EF	Yes (unidirectional)	Yes (unidirectional)
HPC → EF	Yes (unidirectional)	Yes (unidirectional)
GDP → EF	Yes (unidirectional)	Yes (unidirectional)
GDPS → EF	Yes (unidirectional)	Yes (unidirectional)
EF → HC	No	No
TFP → HC	No	No
HPC → HC	No	No
GDP → HC	Yes (unidirectional)	No
HC → TFP	Yes (unidirectional)	Yes (unidirectional)
GDP → TFP	Yes (unidirectional)	Yes (unidirectional)
EF → TFP	No	No
HC → GDP	Yes (unidirectional)	Yes (unidirectional)
TFP → GDP	Yes (unidirectional)	Yes (unidirectional)
HPC → GDP	No	No
HPC → GDPS	Yes (unidirectional)	Not reported
EF → GDP	No	Yes (unidirectional)

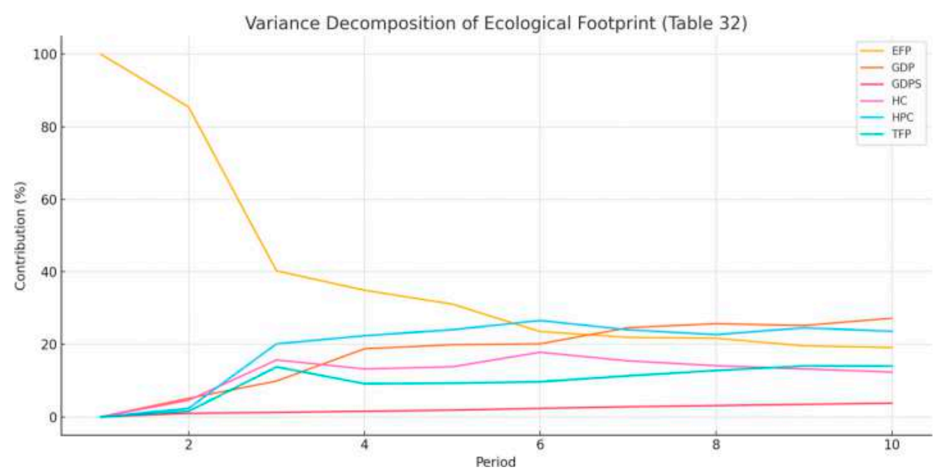
Source(s): Authors' creation based on VECM Granger causality Table 6

Table 8 Variance decomposition of ecological footprint

Period	*S.E. of forecast error*	*EFP*	*HC*	*TFP*	*HPC*	*GDP*	*GDPS*
1	0.0170	100.00	0.00	0.00	0.00	0.00	0.00
2	0.0215	85.43	4.57	1.54	2.35	5.12	0.99
3	0.0352	40.22	15.68	13.77	20.12	9.88	1.23
4	0.0387	34.89	13.21	9.14	22.35	18.77	1.54
5	0.0428	31.05	13.80	9.28	24.01	19.88	1.88
6	0.0484	23.52	17.80	9.67	26.54	20.12	2.35
7	0.0517	21.91	15.43	11.31	23.99	24.57	2.79
8	0.0524	21.65	14.10	12.79	22.65	25.68	3.12
9	0.0558	19.58	13.21	14.04	24.54	25.17	3.46
10	0.0560	19.11	12.35	14.01	23.57	27.18	3.79

Note(s): Forecast variance of the ecological footprint is increasingly driven by GDP, human capital and hydropower over time
Source(s): Authors' estimation

Figure 3 Variance decomposition analysis



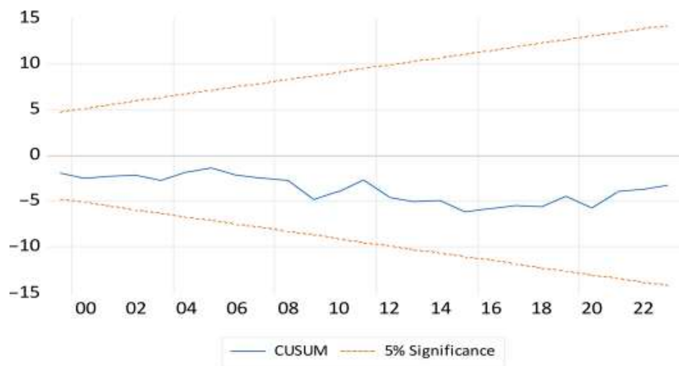
Note: The straight lines represent critical bounds at a 5% significance level
Source: Authors' own work

findings, and further analysis of CUSUM and CUSUMSQ statistics shows that the values remain within critical bounds (Figures 4 and 5).

5. Summary, policy implications and limitations

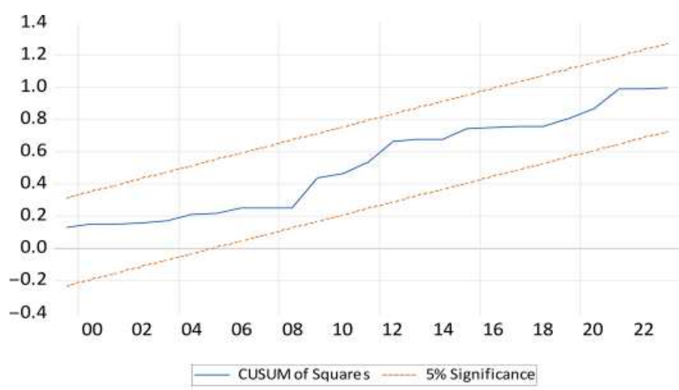
This study advances the literature on sustainable development by empirically assessing how human capital, TFP, HPC and economic growth affect the ecological footprint in India over the period 1980–1981 to 2022–2023. The analysis is theoretically rooted in the Solow growth model, endogenous growth theory, the energy–growth nexus and the EKC. Methodologically, TFP was computed using the Solow residual method. Stationarity of the variables was examined through ADF, PP and Zivot–Andrews unit root tests. The ARDL approach was used to confirm co-integration and estimate long-run and short-run coefficients, while the VECM and variance decomposition techniques were used to analyze causal relationships. CUSUM and CUSUMSQ diagnostics were used to assess model stability.

Figure 4 India: plot of the cumulative sum of the squares of recursive residuals



Note: The straight lines represent critical bounds at a 5% significance level
Source: Authors' own work

Figure 5 Plot of cummulative sum of Squares of recursive residuals



Note: This figure presents the dynamic contribution of explanatory variables to the forecast error variance of the ecological footprint. Over time, the influence of own shocks declines, while GDP, HPC and TFP emerge as key drivers, indicating their growing explanatory power in determining ecological outcomes
Source: Authors' own work

Empirical evidence indicates that human capital significantly reduces the ecological footprint in India over both the short and long run, operating through scale, technique and awareness effects. This suggests that investment in education enhances environmental outcomes by fostering cleaner technologies, reshaping economic structures and cultivating eco-conscious behavior. Conversely, TFP, while central to India's economic expansion, exerts a positive and statistically significant impact on the ecological footprint. These findings suggest that productivity gains in India have historically prioritized economic efficiency over environmental efficiency, largely driven by resource- and energy-intensive technological processes. HPC, although renewable in classification, contributes positively to ecological degradation in India, particularly in ecologically fragile regions, stressing the need to reassess its sustainability credentials. Economic growth worsens the ecological footprint in the initial stages; however, the negative and significant coefficient of its squared term supports the EKC hypothesis in India. The VECM-based Granger causality analysis further supports these findings. The results indicate unidirectional short-run causality from all explanatory variables – human capital, TFP, HPC, economic growth and its squared term – toward the ecological footprint. Human capital also Granger-causes TFP and economic growth, reinforcing its role as a foundational, policy-leveraged variable. The absence of reverse causality from the ecological footprint to macroeconomic variables suggests that environmental degradation has not yet provoked structural policy responses or recalibrations in India's development strategy. The variance decomposition further shows that, over time, the ecological footprint becomes increasingly shaped by external macroeconomic drivers, especially economic growth, HPC, human capital and TFP, rather than its own past behavior.

5.1 Policy implications

The findings point to five core policy imperatives for India's sustainable development agenda. First, environmental sustainability should be mainstreamed into the education system at all levels. Incorporating climate literacy, green skill development and sustainability ethics can enhance the environmental dividends of human capital. Second, given the environmentally regressive nature of current productivity gains, innovation policy must be reoriented to support low-carbon technologies, clean R&D and circular economy principles. Third, hydropower planning should be revisited, especially in biodiversity-rich and seismically sensitive regions. This calls for rigorous environmental impact assessments, community consultations and diversification of renewable energy sources toward solar, wind and decentralized energy systems. Fourth, India should leverage its EKC trajectory by accelerating investment in sustainable infrastructure, strengthening institutional capacity and enforcing environmental regulations to ensure that growth transitions sooner toward the ecological turning point. Finally, the persistent absence of feedback effects from environmental degradation underscores a governance gap. India must adopt an integrated development framework that internalizes ecological constraints into macroeconomic planning, links human capital formation to sustainability outcomes and ensures that environmental health is treated not as a peripheral concern but as a central pillar of long-term economic resilience.

5.2 Limitations and further research potential

Despite its contributions, this study has certain limitations. It is constrained by the availability and granularity of time-series data, limiting the capture of short-term fluctuations and regional diversity. The applied econometric methods (e.g. ARDL and VECM) are suitable for linear analysis but may miss complex nonlinear interactions. Additionally, the focus on macroeconomic and environmental variables overlooks the roles of institutional and sociopolitical factors. Future research can address these gaps by applying machine learning and deep learning techniques to improve predictive power and uncover hidden patterns. Using high-frequency or panel data across Indian states or similar developing economies can enhance robustness. Further studies may also explore the effects of institutional quality, climate policy and behavioral factors on environmental outcomes.

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