

Contents Lists Available At [sddubidsjplm.com](http://sddubidsjplm.com)

# Journal of Planning and Land Management

Journal homepage: [www.sddubidsjplm.com](http://www.sddubidsjplm.com)

DOI:10.36005/jplm.v3i1.89

## Application of the STIRPAT Model in unravelling Carbon Dioxide (CO<sub>2</sub>) emission patterns in the India and Global scales

K. Nirmal Ravi Kumar<sup>1</sup>; M. S. Madhav<sup>2</sup>; N. T. Krishna Kishore<sup>3</sup>; K. Vijay Krishna Kumar<sup>4</sup>; Adinan B. Shafiwu<sup>5</sup> Ishaque Mahama<sup>6\*</sup>

<sup>1</sup>Department of Agric. Economics, Agricultural College, Bapatla, Acharya NG Ranga Agricultural University (ANGRAU), Government of Andhra Pradesh, India, ([kn.ravikumar@angrau.ac.in](mailto:kn.ravikumar@angrau.ac.in))

<sup>2</sup>ICAR-Central Tobacco Research Institute, Rajamahendravaram - 533 105. Andhra Pradesh, ([director.ctr@icar.gov.in](mailto:director.ctr@icar.gov.in))

<sup>3</sup>Institute of Agri-Business Management, S.V. Agricultural College, Tirupati, ANGRAU, Government of Andhra Pradesh, India. ([nt.krishnakishore@angrau.ac.in](mailto:nt.krishnakishore@angrau.ac.in))

<sup>4</sup>Department of Plant Pathology, Agricultural College, Rajamahendravaram, ANGRAU, India ([kotamvk@angrau.ac.in](mailto:kotamvk@angrau.ac.in))

<sup>5</sup>Department of Agricultural and Food Economics, University for Development Studies, Ghana, ([shafiwu@uds.edu.gh](mailto:shafiwu@uds.edu.gh))

<sup>6\*</sup>Corresponding Author, Department of Applied Statistics, Simon Diedong Dombo University of Business and Integrated Development Studies, Wa, Ghana. ([imahama@ubids.edu.gh](mailto:imahama@ubids.edu.gh))

### ARTICLE INFO

#### Article history:

Received: 21 February 2024

Received in revised form: 26 May 2024

Accepted: 27 May 2024

#### Keywords:

Kaya's equation, STIRPAT, Carbon dioxide emissions, Ridge Regression, Population

### ABSTRACT

This study explores the significance of Kaya's Identity in understanding and addressing CO<sub>2</sub>-emissions (CO<sub>2</sub>-emi) in both India and globally, utilising FAOSTAT data from 1991 to 2021. Kaya's Identity breaks down CO<sub>2</sub>-emi into population, GDP per capita (GDP-PC), emissions intensity (EI), and CO<sub>2</sub>-Emissions Intensity (CO<sub>2</sub>-EI). The STIRPAT model was used to analyse these factors, with Ridge regression applied to address multicollinearity. The findings highlight that population growth is a major driver of emissions, with increases of 4.14% in India and 21.36% globally. India's GDP-PC growth of 7.69%, compared to 3.67% globally, also significantly contributes to emissions. Despite improvements in energy efficiency and transitions to renewable energy, CO<sub>2</sub>-emi rose by 6.46% in India and 2.29% globally. The study identifies positive associations between population growth and GDP-PC with CO<sub>2</sub>-emi, while EI and CO<sub>2</sub>-EI show negative associations. Forecasts suggest that in India, sustained GDP-PC growth initially curbed CO<sub>2</sub>-emi, but post-2080, rising population and energy demands accelerated emissions. Globally, consistent GDP-PC growth initially slowed emissions, but after 2000, population growth and increased energy consumption led to a significant surge, driven by slower economic expansion and higher fossil fuel use. The results also indicate a long-term cointegration relationship between CO<sub>2</sub>-emi and the selected variables at both the all-India and global levels. The significantly negative coefficient for CO<sub>2</sub>-emi lagged by one period (CO<sub>2</sub>emi(-1)) suggests a strong long-run adjustment mechanism both at the all-India and global levels. This study underscores the need for integrated strategies addressing population growth, GDP-PC, energy efficiency, and clean energy adoption to combat climate change sustainably. Policymakers should focus on emerging technologies such as carbon capture, understanding consumer behaviour's impact on emissions, analysing regional disparities, and developing long-term emissions scenarios. JEL classification: Q54, Q56, Q58.

## 1. Introduction

In the contemporary global landscape, harmonising economic development and environmental sustainability has become a defining imperative for countries worldwide. This multifaceted challenge is exacerbated by the urgent need to

address climate change, a global issue that transcends geographic and political boundaries. It requires a profound transformation in the way nations approach economic growth, sustainability, and the well-being of their populations. Climate change, primarily driven by the accumulation of greenhouse gases in Earth's atmosphere, poses an existential

threat to our planet. The consequences of climate change include rising global temperatures, extreme weather events, and disruptions to ecosystems (Krishnan *et al.*, 2020; Mohanty & Wadhawan, 2021). The prevailing scientific consensus unequivocally underscores the imperative for immediate measures aimed at constraining global warming and alleviating the adverse repercussions of climate change (Nathaniel *et al.*, 2022). Simultaneously, a compelling and time-sensitive exigency persists for fostering economic advancement in nations across the globe. Throughout history, economic growth has functioned as a catalyst for advancement, elevating multitudes from impoverishment, widening the reach of educational and healthcare resources, and improving standards of living. For many nations, particularly those with large populations and significant development challenges, fostering economic growth is not a mere aspiration; it is a fundamental necessity to secure a better future for their citizens. The crux of this challenge lies in finding a harmonious equilibrium between these two imperatives—sustaining economic development while curtailing carbon dioxide (CO<sub>2</sub>) emissions (CO<sub>2</sub>-emi). Achieving this balance requires a fundamental shift in the way we conceive and implement economic policies, environmental stewardship, and social progress.

India is at a critical juncture, grappling with a complex and multifaceted challenge that demands innovative solutions. As one of the world's fastest-growing economies, it faces a confluence of unique circumstances driven by its vast population, ambitious development objectives, and growing environmental concerns. At its core, this challenge revolves around balancing robust economic growth with an imperative to reduce CO<sub>2</sub>-emi, a dilemma that resonates globally but carries distinctive contours in India due to its demographic and socio-economic dynamics (Nikunj & Dhyani, 2023).

Kaya identity analysis serves as a potent framework for disentangling the fundamental drivers of CO<sub>2</sub>-emi, offering invaluable insights to policymakers and researchers alike (Metz *et al.*, 2007). This study employed Kaya identity analysis to encompass a global perspective and hone in on India's unique context. By doing so, this study endeavours to illuminate the precise factors underpinning CO<sub>2</sub>-emi. Moreover, it delves into the indispensable prerequisites essential for nurturing sustainable and environmentally responsible economic growth within India, drawing upon valuable lessons derived from global experiences. According to Kaya's identity, CO<sub>2</sub>-emi can be expressed as the product of four primary determinants: population (P), gross domestic product per capita (GDP-PC), energy intensity (EI), and CO<sub>2</sub>-Emissions Intensity (CO<sub>2</sub>-EI). Analysing these factors reveals crucial insights into the dynamics of CO<sub>2</sub>-emi and the paths to sustainable development (WRI, 2018).

In India, population growth emerges as the most influential factor, with a 3.0031% increase in emissions associated with a 1% rise in the annual growth rate. This underscores the pressing need for sustainable urban planning, energy-efficient infrastructure, and clean energy solutions to accommodate a growing population while mitigating CO<sub>2</sub>-emi. GDP-PC also plays a substantial role, indicating that economic development often leads to increased CO<sub>2</sub>-emi, indicating a delicate balancing act for policymakers, necessitating investments in green technologies and sustainable industrial

practices. The impact of EI underscores the importance of energy efficiency measures to reduce emissions while fostering economic growth. Meanwhile, the smaller impact of CO<sub>2</sub>-EI emphasises the potential for transitioning to cleaner energy sources. Overall, the findings highlight the complexity of the emissions equation and the necessity of a holistic approach that integrates population control, economic development, and sustainable energy practices to effectively address India's emissions challenges (Beşer & Hızarc, 2017; Adebayo *et al.*, 2020; Erum & Shazia, 2022). On the global scale, similar trends emerge, with a higher global population associated with increased CO<sub>2</sub>-emi, underscoring its substantial impact on emissions. Increased GDP per capita also positively affects CO<sub>2</sub>-emi, highlighting the role of economic prosperity. In addition, lower energy intensity and reduced CO<sub>2</sub>-EI are linked to lower global CO<sub>2</sub>-emi, stressing the importance of energy efficiency and cleaner energy sources (Rehman *et al.*, 2022).

This study on trends in variables within Kaya's identity and determinants for CO<sub>2</sub>-emi at both India and global levels holds profound significance. It serves as a beacon for informed policymaking, offering critical insights into the intricate web of factors influencing CO<sub>2</sub>-emi. The dual focus on India and global contexts ensures its relevance and applicability beyond borders. Therefore, this study addresses a global imperative—how to balance economic development with emissions reduction to combat climate change. By dissecting Kaya's identity, it unveils the key drivers of CO<sub>2</sub>-emi, highlighting the pivotal roles played by population growth, GDP-PC, EI, and CO<sub>2</sub>-EI. These findings are instrumental in shaping evidence-based policies aimed at achieving sustainable development while curbing emissions. Moreover, the study contributes to the global discourse on climate change mitigation, emphasising the urgency of understanding and acting upon the factors that propel CO<sub>2</sub>-emi. The alignment of this study with the Sustainable Development Goals, particularly climate action and affordable and clean energy, underscores its role in advancing global sustainability. It delves into the interconnectedness of variables within Kaya's identity, emphasising the necessity of holistic approaches to emissions reduction. The significance of these findings lies in their applicability not only to India but also to countries worldwide facing the dual challenges of economic development and emissions reduction. Balancing these goals requires innovative solutions, such as investments in renewable energy, sustainable practices in various sectors, and policy frameworks that promote sustainable growth.

## 2. Review of literature

### 2.1. Theoretical literature

Kaya Identity, named after Kaya and Yokoburi, is a mathematical expression that represents total CO<sub>2</sub>-emi or environmental impact (I) as a product of four factors namely: human population (P), GDP-PC, EI (measured as energy use per unit of GDP), and CO<sub>2</sub>-EI (CO<sub>2</sub>-emi produced per unit of energy consumed) (Kaya & Yokoburi, 1997). This identity offers a concrete formulation of the more general IPAT model that was developed by Ehrlich and Holdren (1971) in the seventies, which was criticised. This was because the model did not allow for empirical analysis. Furthermore, the model operated under the assumption that each variable contributed

to the same proportional effect. Recognising these limitations, Dietz and Rosa (1997) addressed this issue by reformulating the Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model as an extension of the IPAT model. They transformed it into a stochastic model, which provided a more robust framework for empirical analysis and hypothesis testing.

## 2.2. Empirical Literature:

Dawit and Zerayehu (2018) employed an integrated approach based on the IPAT identity and VECM framework. Their study aligns with the Malthusian perspective, suggesting a significant positive long-term relationship between population growth and CO<sub>2</sub>-emi, with findings indicating that a 1% increase in population results in a 1.9% increase in CO<sub>2</sub>-emi in Ethiopia. This underscores the need for policies addressing population pressures to facilitate sustainability initiatives. Similarly, González *et al.* (2021) applied the Kaya Identity to both OECD and non-OECD regions, examining the impact of economic crises on emissions. They found that emissions peaked in most countries before or during recessions, driven by decreased economic growth and reduced energy/carbon intensity. Their study identifies key decarbonization drivers and emphasizes the urgency of actions to limit global temperature increases to 1.5°C.

Dawit and Zerayehu (2018) conducted an empirical investigation in Ethiopia, finding a direct correlation between population growth and increased CO<sub>2</sub>-emi, highlighting the urgent need for policies addressing population pressures. Li and Jiang (2019) focused on CO<sub>2</sub>-emi in Russia, revealing that economic recessions historically reduced emissions, but shifts to less carbon-intensive fuels and a declining population also played significant roles. They observed a decoupling between economic activity and CO<sub>2</sub>-emi in the 21st century, suggesting potential for sustainable economic growth. González *et al.* (2021) empirically applied the Kaya Identity, finding that economic downturns led to reduced emissions, underscoring the role of structural changes and energy conservation. Vivid and Deni (2021) analysed the ASEAN region using the Kaya Identity from 1990 to 2017, revealing that population growth, economic activity, and carbon intensity increased CO<sub>2</sub>-emi, while energy intensity reduced emissions in some countries. This study highlights the varying impacts of economic activity and energy intensity across income groups in ASEAN countries. Lastly, Sarvar *et al.* (2023) focused on Russia, finding that both GDP and fossil fuel usage intensity positively impact CO<sub>2</sub>-emi, with projections indicating rising emissions until 2030 under a business-as-usual scenario. This underscores the need for substantial policy interventions to meet emission reduction targets.

The reviewed literature, both theoretical and empirical, underscores the complex and multifaceted dynamics of CO<sub>2</sub>-emi across different regions and contexts. The theoretical contributions, such as the work by Dawit and Zerayehu (2018) and González *et al.* (2021), provide foundational perspectives on how population growth and economic crises impact emissions. The empirical studies, including those by Li and Jiang (2019), Vivid and Deni (2021), and Sarvar *et al.* (2023), offer concrete data and findings that highlight the specific drivers and impacts of CO<sub>2</sub>-emi in various settings, from Ethiopia and Russia to the ASEAN region. Together,

these studies emphasize the urgent need for tailored policy interventions to manage population growth, transition to cleaner energy sources, and decouple economic growth from CO<sub>2</sub>-emi. By providing a comprehensive understanding of these dynamics, the literature serves as a crucial knowledge base for policymakers, environmental advocates, and industries aiming to foster a sustainable and environmentally responsible future.

## 3. Methodology

Kaya Identity (Kaya & Yokoburi, 1997) is a mathematical expression that represents total CO<sub>2</sub>-emi or environmental impact (I) as a product of four factors (Equation 1): human population (P), GDP-PC, EI (measured as energy use per unit of GDP), and CO<sub>2</sub>-EI (CO<sub>2</sub>-emi produced per unit of energy consumed). This identity offers a concrete formulation of the more general I (CO<sub>2</sub>-emi) = PAT equation (Ehrlich & Holdren, 1971), which relates various factors determining the extent of human impact. Here, impact (I) is the result of the interaction of the total population (population/P), welfare (affluence/(A)) expressed as GDP-PC, and technology (T)) involved in supporting each unit of consumption (Giambona *et al.*, 2005; Andreas, 2013).

$$CO_2 \text{ emissions} = Population * \frac{GDP}{Population} * \frac{Energy \text{ consumption}}{GDP} * \frac{CO_2 \text{ emissions}}{Energy \text{ consumption}} \quad (1)$$

where,  $\frac{GDP}{Population} = \text{GDP-PC}$ ;  $\frac{Energy \text{ consumption}}{GDP} = \text{EI}$  and  $\frac{CO_2 \text{ emissions}}{Energy \text{ consumption}} = \text{CO}_2\text{-EI}$ .

The multiplicative identity framework of IPAT presents challenges for empirical analysis, as the terms of (1) theoretically cancel each other out. Furthermore, this model is not well-suited for hypothesis testing because it operates under the assumption that each variable contributes to the same proportional effect. Recognising these limitations, Dietz and Rosa (1997) addressed this issue by reformulating the Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model as an extension of the IPAT model (Equation 1). They transformed it into a stochastic model, which provided a more robust framework for empirical analysis and hypothesis testing, as in Equation 2:

$$CO_2 \text{ emissions} = aP^{\beta_1}GDP^{\beta_2}EI^{\beta_3}CO_2EI^{\beta_4}\epsilon \quad (2)$$

where, P, GDP-PC, EI and CO<sub>2</sub>-EI are the same as in IPAT equation (1);  $\beta_1$ ,  $\beta_2$ ,  $\beta_3$  and  $\beta_4$  are the coefficients, and  $\epsilon$  is the error term. With this reformulation, data on CO<sub>2</sub> emissions (Kilotonnes), P (Billion), GDP-PC(US\$), EI (Terajoule/US\$), and CO<sub>2</sub>-EI (Kilotons/Terajoule) are used to estimate  $\beta_1$ ,  $\beta_2$ ,  $\beta_3$ ,  $\beta_4$  and  $\epsilon$  using the regression methods of statistics. Data are obtained from FAOSTAT for the period 1991-2021 at both the Indian and global levels. Thus, with the reformulated version, the IPAT model is converted into a general linear model to which statistical methods can be applied, and the non-proportionate importance of each influencing factor may be assessed. Given in logarithmic form (York *et al.*, 2003), (2) is given as follows:

$$\log CO_2 - emi = \log a + \beta_1 \log P + \beta_2 \log GDP-PC + \beta_3 \log EI + \beta_4 \log CO_2-EI + \ln \epsilon \quad (3)$$

Equation (3) allows the estimation of the terms as respective elasticities, and the coefficients are expressed as percentage changes. Coefficients approaching unity indicate unit elasticity, signifying a proportional change in the dependent variable resulting from alterations in the independent variable.

### 3.1 Ridge regression

When applied to real-world data, the STIRPAT model is estimated *via* ordinary least squares (OLS) and often encounters multicollinearity issues, posing a significant challenge to the reliability of coefficient estimates. By tailoring the conventional OLS regression method, we introduce a distinctive approach that permits a controlled degree of bias in estimating regression coefficients. Although this entails biased estimation, it brings forth a profound advantage: the introduction of a minimal bias, represented by the k-value, can substantially enhance the accuracy of coefficient estimation while concurrently reducing the overall mean absolute error (MAE). Moreover, the incremental adjustment of the k-value exerts a discernible influence on the coefficient's trajectory, effectively nudging it closer to zero. Notably, a k-value of zero ( $k = 0$ ) allows for a seamless transition back to OLS estimation (Xiong *et al.*, 2020; Zhao *et al.*, 2022).

Ridge regression augments the stability of the regression model and bestows several key benefits. It consistently yields lower values of MAE and standard error (SE) than those of OLS. Consequently, the estimation outcomes are more stable and exhibit a heightened proximity to the true underlying values. It strikes a delicate balance between variance reduction and controlled bias, empowering researchers to extract more robust, interpretable insights from STIRPAT models (Feng, 2017). This transformative technique, as elucidated by Hoerl and Kennard (1970), underscores its potential to refine and enhance the precision of regression analysis:

$$Y = X\beta + \epsilon \quad (4)$$

where X represents the design matrix,  $\beta$  symbolises the unstandardized coefficient matrix of the regression equation, and  $\epsilon$  denotes the constant matrix. The OLS estimation for  $\beta$  is given by the formula:

$$\hat{\beta}_{OLS} = (X'X)^{-1} X'Y \quad (5)$$

However, when multicollinearity among independent variables emerges, causing  $|X'X|$  to approximate zero, the OLS method becomes ineffective because it cannot compute the inverse matrix. In response to this challenge, Ridge regression (Hoerl, 1962), despite its bias, addresses this issue by introducing a positive scalar, k, multiplied by the identity matrix, kI, to  $X'X$ . Consequently,  $|X'X + kI| \neq 0$ .

To ensure uniformity in data dimensions, standardisation is often employed, resulting in X representing the standardised design matrix. Ridge regression estimation, denoted as  $\hat{\beta}(k)$

=  $|X'X + kI|X'Y$ , offers increased stability compared with OLS. Here, k serves as the ridge parameter and  $\hat{\beta}(k)$  demonstrates enhanced stability in estimation when compared with OLS.

A key property of ridge regression estimation lies in its ability to minimise MSE using a positive scalar 'k', such that:

$$\begin{aligned} &MSE(\hat{\beta}(k)) < MSE(\hat{\beta}) \\ &\text{namely,} \\ &\sum_{j=1}^p E(\hat{\beta}_j(k) - \beta_j)^2 < \sum_{j=1}^p D(\hat{\beta}_j) \end{aligned} \quad (6)$$

When the ridge parameter (k) varies within the range of (0,  $\infty$ ), the resulting estimates for  $\beta$ , denoted as  $\hat{\beta}_j(k)$  become functions of k. These functions can be graphically represented on a coordinate plane, forming what is commonly referred to as the 'ridge trace' curve. In practical empirical analyses, the k values typically span the interval from 0 to 1, with step lengths of 0.01, 0.05, or 0.1 employed in the ridge regression method. By observing the shape and trajectory of the ridge trace curve, researchers can discern the most suitable value for k. This selection process aids in the identification of independent variables to be included in the final model equation. This approach serves a dual purpose: it effectively mitigates the impact of multicollinearity, thereby enhancing the model's precision and explanatory power, while also offering valuable insights into the relationships of the independent variables within the model.

To forecast CO<sub>2</sub>-emi for both India and global scenarios, the Kaya Identity Scenario Prognosticator developed by the University of Chicago was employed (IPCC, 2018). This sophisticated tool aids in predicting emissions trends and trajectories, thus contributing to a comprehensive analysis of CO<sub>2</sub>-emi dynamics.

To analyse the long-run cointegration among the selected variables, an Error Correction Model (ECM)-long-run test is specified. By employing a linear transformation, ECT is derived from the ARDL bounds test. The negative and statistically significant ECT indicate the speed of adjustment and how quickly the variables return to long-run equilibrium.

## 4. Results and discussion

### 4.1. Trends in the selected variables

#### 4.1.1. Population:

Population growth in India at 4.14% and globally at 21.36% during 1991-2021 has significant implications for CO<sub>2</sub>-emi and environmental sustainability. The relationship between population growth and CO<sub>2</sub>-emi is intrinsic, as a larger population increases the demand for resources, energy, and consumption, thus contributing to higher emissions. Rapid population growth presents several challenges, particularly in a country such as India, regarding resource depletion, heightened pressure on natural resources resulting in deforestation, habitat destruction, and increased CO<sub>2</sub>-emi. Additionally, the growing demand for energy in India often relies on fossil fuels, exacerbating emissions and air pollution. Globally, rapid population growth contributes to CO<sub>2</sub>-emi on a larger scale, worsening the climate crisis and causing global repercussions, such as rising temperatures and extreme weather events. It can also trigger competition for

resources, potentially leading to geopolitical tensions (Chandrima & Kakali, 2016).

Therefore, population growth in India and globally indirectly contributes to CO<sub>2</sub>-emi by amplifying energy consumption. In India, urbanisation, expanding middle-class consumption, and industrial growth driven by a larger population significantly elevate energy demands and emissions (Luqman *et al.*, 2023). On a global scale, a growing population escalates global energy demand, fostering increased reliance on fossil fuels and intensifying competition for finite resources (Anqing, 2001; Bengochea *et al.*, 2006; Adewale *et al.*, 2019; Ahmad *et al.*, 2020). This expansion of energy-intensive activities both within India and globally underscores the critical importance of implementing sustainable strategies, such as renewable energy adoption, energy efficiency measures, and responsible urban planning, to mitigate the indirect impacts of population growth on CO<sub>2</sub>-emi. In the context of population growth's influence on CO<sub>2</sub>-emi, it is imperative to adopt a holistic perspective that encompasses various interconnected variables. Beyond demographic expansion, factors such as GDP, EI, and CO<sub>2</sub>-EI play pivotal roles in shaping emissions trends, both in India and globally.

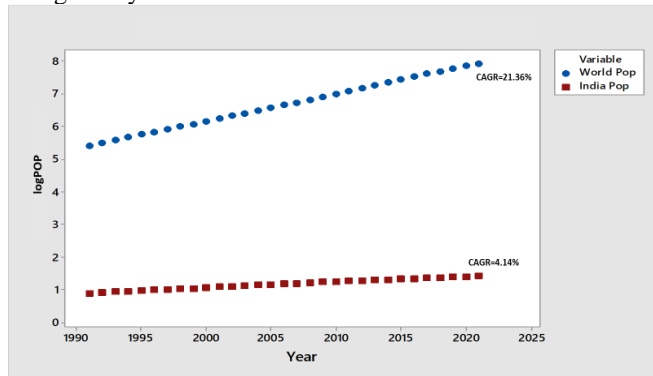


Figure 1: Population growth trends in India vis-à-vis World (1991-2021)

#### 4.1.2. GDP-PC

India's comparatively higher GDP-PC growth rate of 7.69%, in contrast to the global average of 3.67% (Figures 2 and 3), can be attributed to a confluence of intricate factors. India's demographic dividend, characterised by a youthful and expanding working-age population, plays a pivotal role in propelling economic growth and productivity, thereby elevating GDP-PC figures. Moreover, India's proactive economic reforms, exemplified by initiatives like "Make in India" and "Digital India," have attracted investments, spurred innovation, and driven economic expansion, contributing significantly to GDP-PC growth. The dominance of India's services sector, particularly in IT, software, and business process outsourcing, has emerged as a stalwart driver of economic growth, characterised by higher productivity levels and substantial value generation. Additionally, substantial investments in infrastructure projects aimed at enhancing transportation, urban development, and connectivity have the potential to augment productivity, further fuelling GDP-PC growth. Conversely, the global context features a slower growth rate due to demographic factors such as ageing populations, constraining overall economic expansion. Limited access to critical inputs like arable land and energy resources curtailed rapid economic growth in some developed nations. Moreover,

technological saturation in well-established industries can impede productivity gains, contributing to slower GDP-PC growth in advanced economies. Finally, economic cycles, marked by periods of recession or stagnation affecting numerous countries, have a direct impact on GDP-PC growth rates (Rafał, 2015; Bismark & Li, 2018; Mohsin *et al.*, 2019).

#### 4.1.3. EI:

The diverging trends in EI, where India's EI decreased by 2.14% while the global average decreased by 2.52% from 1991 to 2021 (Figures 4 and 5), can be attributed to a combination of factors. India's decreased EI stems from its gradual shift towards a more services-oriented economy, where sectors like information technology and outsourcing play significant roles, inherently consuming less energy compared to heavy industries (Danish *et al.*, 2020). This shift, coupled with investments in energy-efficient technologies, is driven by policy initiatives such as the National Mission for Enhanced Energy Efficiency (NMEEE) and the active expansion of renewable energy sources that have led to reductions in EI (Rahiman *et al.*, 2019). In contrast, the global decrease in EI reflects a broader international commitment to improving energy efficiency. Developed economies, facing resource constraints and environmental concerns, have focused on technological advancements and stringent environmental regulations, contributing to EI reductions. Furthermore, the global transition towards service-oriented economies has played a role in decreasing EI, mirroring India's experience. While both India and the world are making notable strides in energy efficiency, continued efforts and innovation in sustainable practices remain essential to mitigate the environmental impact of economic activities on a global scale (Mirza *et al.*, 2022).

#### 4.1.4. CO<sub>2</sub>-EI

The diverging trends in CO<sub>2</sub>-EI, with India experiencing a 0.39% decrease while the global average decreases by a smaller margin of 0.05% from 1991 to 2021 (Figures 6 and 7), underscore the nuanced dynamics at play in CO<sub>2</sub>-emi management. India's reduced CO<sub>2</sub>-EI can be attributed to several key factors (Melisa, 2022). First, India has actively expanded its renewable energy capacity, encompassing solar, wind, and hydropower, which has effectively lowered the carbon intensity of energy production. Additionally, efforts to curtail emissions have led to the adoption of cleaner technologies and improved energy efficiency across various sectors, ultimately resulting in decreased CO<sub>2</sub>-EI consumption. The gradual transition towards natural gas as a cleaner energy source has further contributed to India's lower carbon intensity.

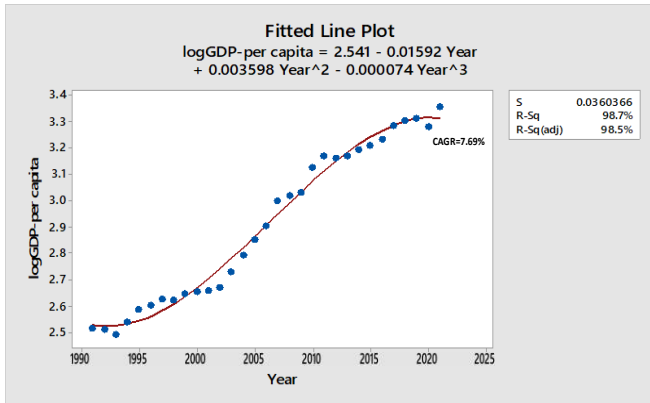


Figure 2: Trends in GDP -per capita in India (1991 -2021)

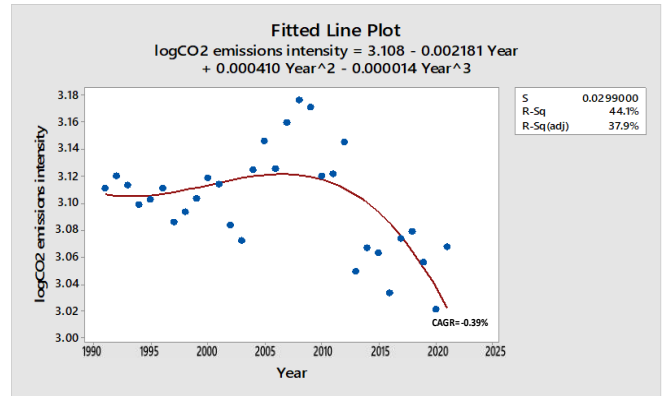


Figure 6: Trends in CO2 Emissions Intensity in India (1991 -2021)

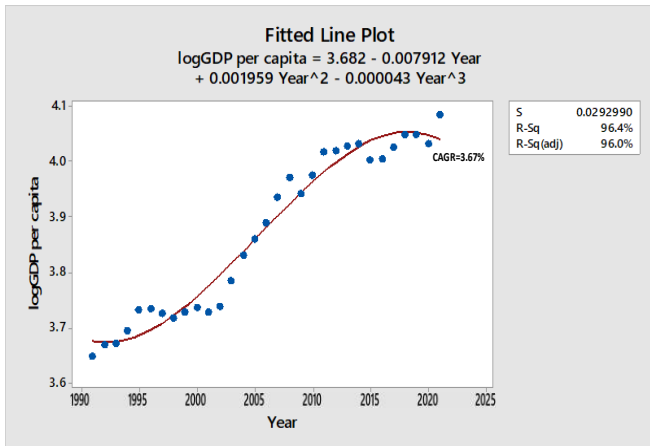


Figure 3: Trends in GDP -per capita in World (1991 -2021)

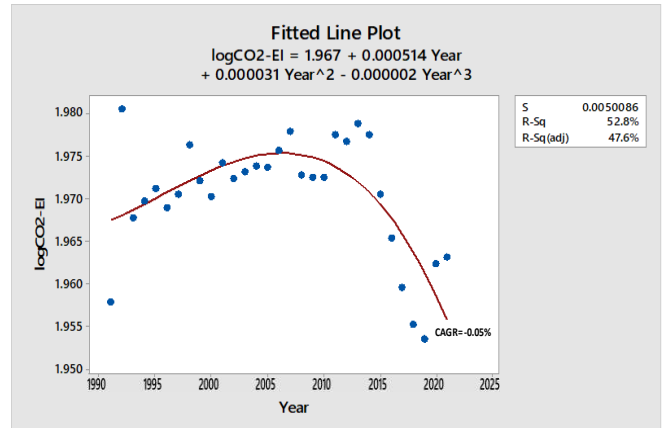


Figure 7: Trends in CO2 Emissions Intensity in World (1991 -2021)

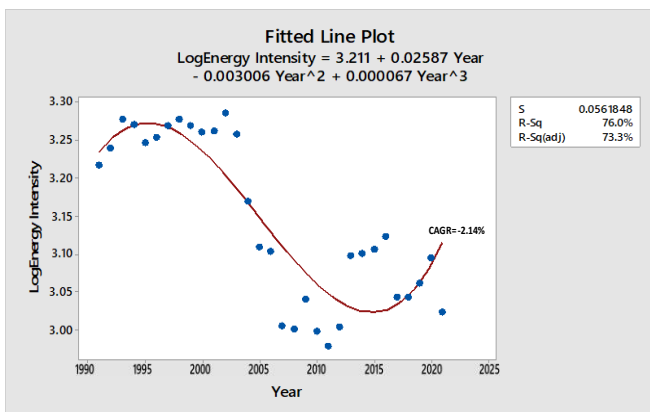


Figure 4: Trends in Energy Intensity in India (1991 -2021)

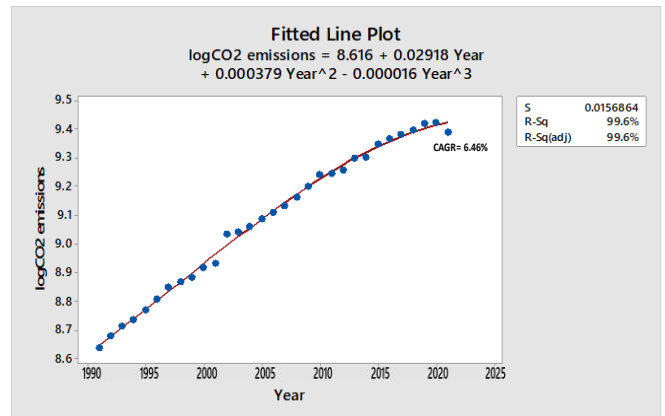


Figure 8: Trends in CO2 Emissions from India (1991 -2021)

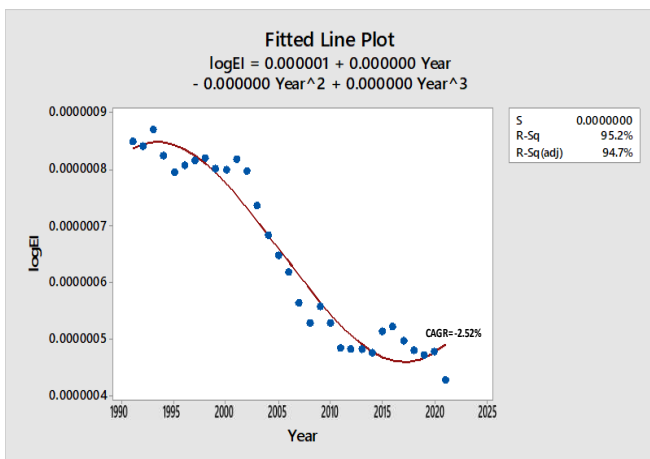


Figure 5: Trends in Energy Intensity in World (1991 -2021)

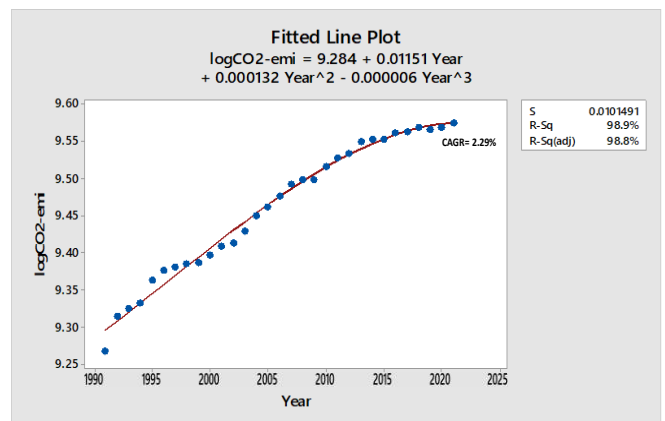


Figure 9: Trends in CO2 Emissions from World (1991 -2021)

Furthermore, supportive policy initiatives and incentives from the government have promoted emissions reduction strategies (Xiongfeng *et al.*, 2019; Ziroat & Raufhon, 2022). On a global scale, the decrease in CO<sub>2</sub>-EI indicates broader international efforts to combat climate change. The widespread adoption of renewable energy sources is instrumental in reducing CO<sub>2</sub>-emi. Advancements in energy efficiency technologies and practices, particularly in the industrial and manufacturing sectors, have also contributed to the global decrease in CO<sub>2</sub>-EI. Stringent environmental regulations in numerous countries have incentivized industries toward cleaner energy sources and technologies, aligning with the global commitment to environmental sustainability (Congjun *et al.*, 2023).

While both India and the rest of the world are making commendable progress in reducing CO<sub>2</sub>-EI, the imperative remains to sustain and amplify these efforts. Prioritizing renewable energy adoption, energy efficiency measures, and emissions reduction strategies is essential for a sustainable, low-carbon future.

#### 4.1.5. CO<sub>2</sub>-emi

The significant increase in CO<sub>2</sub>-emi by 6.46% in India, compared to the global increase of 2.29% from 1991 to 2021 (Figures 8 and 9), reflects a complex interplay of factors specific to India's socioeconomic landscape. India's rapid economic growth, marked by increased industrialization, urbanisation, and growing consumer demand, has been a primary driver of higher CO<sub>2</sub>-emi (Parikh *et al.*, 2009, IPCC, 2022). This economic expansion has correlated with elevated energy consumption, particularly in sectors such as industry and transportation, where fossil fuels like coal and oil continue to dominate (Liddle 2011; Ratanavaraha *et al.*, 2015; Shahbaz *et al.*, 2017). Furthermore, as India undergoes significant development and infrastructure expansion to meet the needs of its growing population, emissions from construction and manufacturing activities have risen. The agriculture sector, which is crucial to India's economy, also contributes to emissions, notably through practices that release methane (Leena, 1997; Jayanarayanan *et al.*, 2022).

On the global front, while CO<sub>2</sub>-emis have increased, the growth rate has been relatively lower due to variations in economic growth among countries. Developed economies with slower growth rates have experienced more stable emissions patterns. Additionally, a shift towards cleaner energy sources in several countries, coupled with investments in energy efficiency, has mitigated emissions growth. Stringent environmental policies and regulations in some nations have further incentivized industries to adopt cleaner technologies. Advancements in energy-efficient practices in sectors like transportation and industry have also played a role in controlling emissions (Crippa *et al.*, 2022).

The divergence between India's higher CO<sub>2</sub>-emi growth and the global average underscores the unique challenges faced by emerging economies like India. Balancing the imperatives of economic development, energy access, and environmental sustainability remains a multifaceted challenge. India's journey towards environmental sustainability and climate responsibility necessitates concerted efforts to curb emissions

growth while fostering economic prosperity and improving the quality for life of its burgeoning population.

#### 4.2. Determinants of CO<sub>2</sub>-emi

The trends in factors influencing CO<sub>2</sub>-emi in India and globally (Figures 10 and 11) reveal intricate dynamics shaping emissions patterns. Population growth exerts a significant and positive influence on CO<sub>2</sub>-emi, underscoring the role of demographic expansion in driving emissions. In India, rapid population growth intensifies resource demand, deforestation, and CO<sub>2</sub>-emi. Globally, a larger population contributes to higher emissions, exacerbating the climate crisis and resource competition (Casey & Oded, 2016; Cui *et al.*, 2017; Wu *et al.*, 2019; Zhao *et al.*, 2022).

GDP-PC demonstrates a positive and significant influence on CO<sub>2</sub>-emi (Figures 12 and 13), indicating that economic growth is linked to emissions increases in India and the rest of the world. India's comparatively higher GDP-PC growth results from a youthful population, economic reforms, and a dominant services sector, contributing to emissions growth. Globally, variations in economic growth rates among countries have led to differing emissions patterns, with developed economies exhibiting slower growth and more stable emissions (Du *et al.*, 2012; Shah *et al.*, 2022; Zhao *et al.*, 2022).

EI, represented by the ratio of energy consumption to GDP, exerts a negative influence on CO<sub>2</sub>-emi in India and globally (Figures 14 and 15), emphasising the importance of energy efficiency in emissions mitigation. India's decreasing EI suggests a shift towards a services-oriented economy and investments in energy-efficient technologies and renewables. Globally, the reduction in EI reflects international efforts to enhance energy efficiency through technological advancements and stringent environmental regulations (Susan, 2011; Zhao *et al.*, 2022). This has been confirmed by many studies, such as Du *et al.* (2012), and Dong *et al.* (2019).

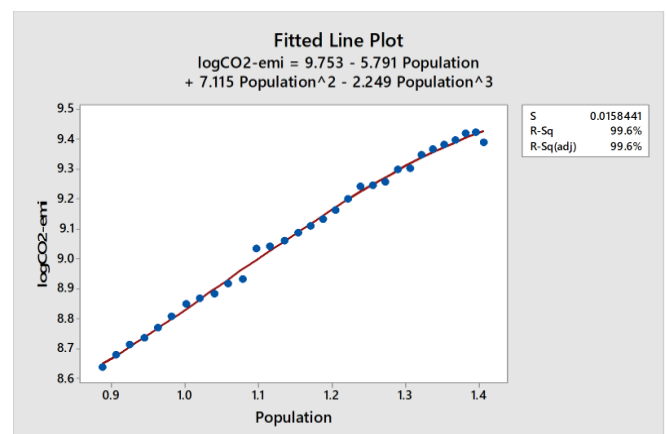


Figure 10: Influence of Population growth on CO<sub>2</sub> Emissions in India (1991-2021)

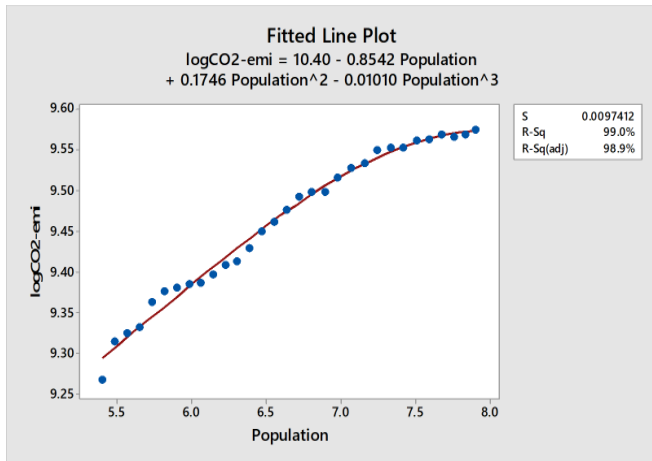


Figure 11: Influence of Population growth on CO<sub>2</sub> Emissions in World (1991-2021)

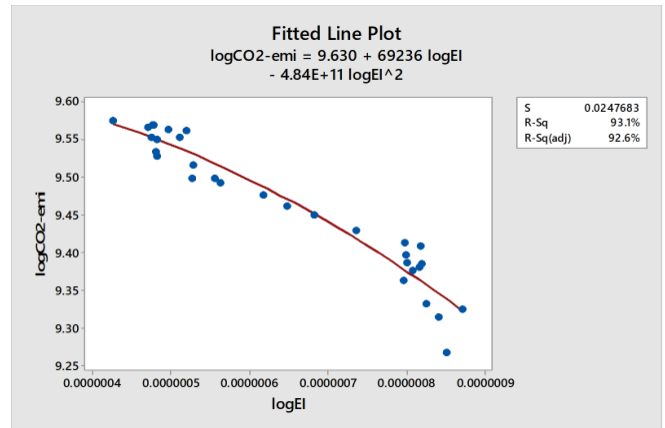


Figure 15: Influence of Energy Intensity on CO<sub>2</sub> Emissions in World (1991-2021)

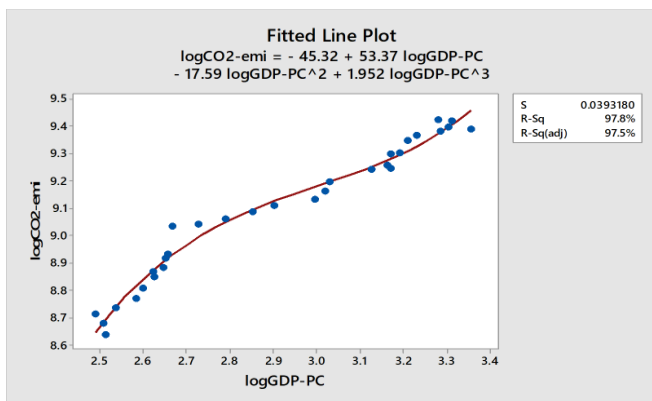


Figure 12: Influence of GDP-per capita on CO<sub>2</sub> Emissions in India (1991-2021)

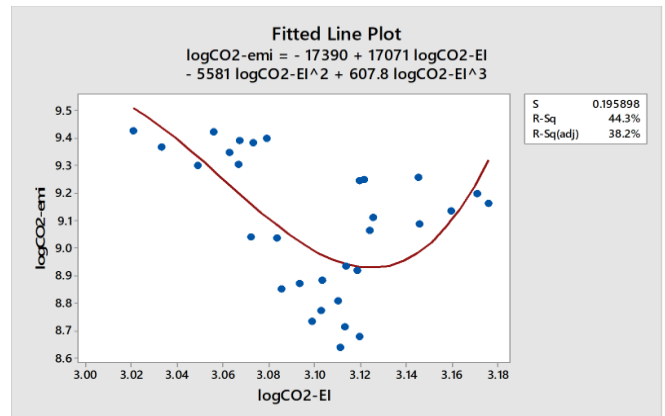


Figure 16: Influence of CO<sub>2</sub> Emissions Intensity on CO<sub>2</sub> Emissions in India (1991-2021)

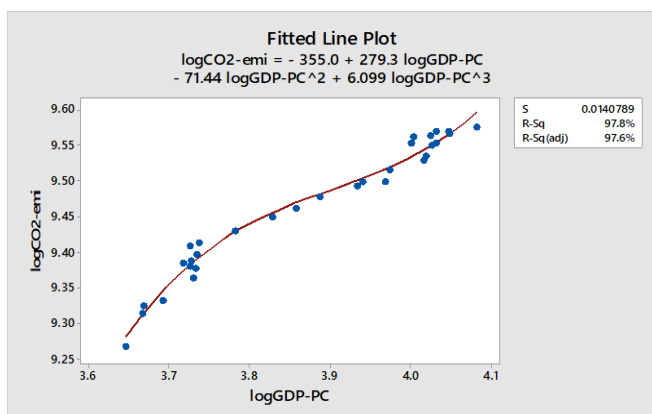


Figure 13: Influence of GDP-per capita on CO<sub>2</sub> Emissions in World (1991-2021)

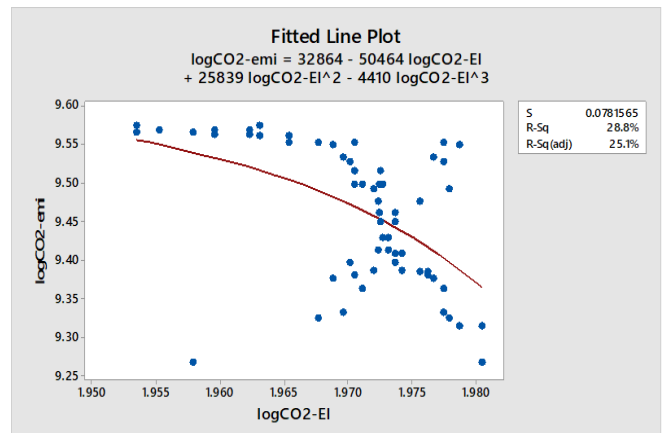


Figure 17: Influence of CO<sub>2</sub> Emissions Intensity on CO<sub>2</sub> Emissions in World (1991-2021)

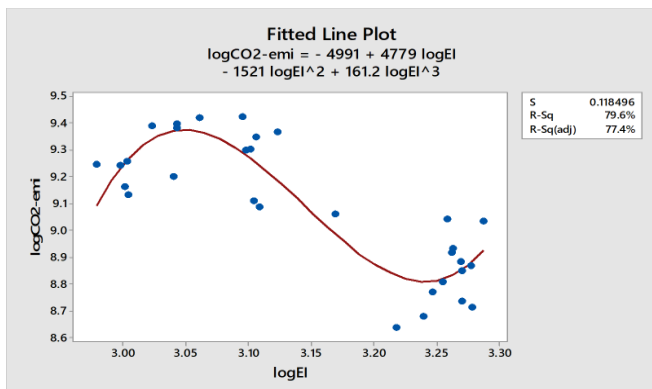


Figure 14: Influence of Energy Intensity on CO<sub>2</sub> Emissions in India (1991-2021)

The influence of CO<sub>2</sub>-EI varies between India and the global context (Figures 16 and 17). In India, it initially showed a negative influence on emissions but has recently turned positive, indicating challenges in maintaining emissions progress. This shift is attributed to rapid economic growth, reliance on coal, infrastructure development, emissions from various sectors, and agricultural practices (Malhi *et al.*, 2021). Addressing this challenge requires a multifaceted approach, including cleaner technologies, policy consistency, sustainable urban planning, and public engagement. Globally, CO<sub>2</sub>-EI continues to exert a negative influence on CO<sub>2</sub>-emi reflecting the adoption of renewables, energy efficiency advancements, and environmental regulations. However, the small decrease in global emissions intensity highlights the need for sustained efforts to reduce emissions associated with economic activities (Wei *et al.*, 2017; Dolf *et al.*, 2019; Li *et*



al., 2021). These trends underscore the complex interplay of factors that shape emissions patterns. While population growth and economic expansion drive emissions, boosting energy efficiency and emissions intensity are crucial for mitigating environmental impacts. The recent positive influence of CO<sub>2</sub>-EI in India emphasises the need for sustained emissions reduction efforts. On a global scale, the reduction of CO<sub>2</sub>-EI is crucial for a sustainable, low-carbon future.

Integrated Science Assessment Model for Atmospheric CO<sub>2</sub> (ISAMpCO<sub>2</sub>) forecasts for India (Figures 18 and 19) and the global context (Figures 20 and 21) reveal alarming trajectories of CO<sub>2</sub>-emi, demanding immediate and comprehensive action to combat climate change. In India, GDP-PC consistently followed an upward trajectory throughout the specified reference period. This sustained economic growth played a role in mitigating both EI and CO<sub>2</sub>-EI, as both indicators exhibited a declining trend. Consequently, CO<sub>2</sub>-emi experienced a relatively gradual increase until 2080. However, beyond this pivotal year, possibly due to population growth and increased energy consumption demands, the ability to effectively counterbalance rising EI and CO<sub>2</sub>-EI diminished. Consequently, the trajectory of CO<sub>2</sub>-emi began to exhibit a rapid escalation from 2080 onwards (Figure 18). These forecasts illustrate a dramatic surge in emissions from 2025 to 2100, driven by rapid industrialization, urbanisation, and heightened consumer demand, which fuel energy-intensive activities across sectors such as construction, manufacturing, and transportation. India's historical reliance on coal exacerbates EI. International factors, including economic conditions and energy prices, as well as population dynamics and technological challenges, also influence EI trends. Addressing this monumental challenge requires substantial investments in cleaner technologies, renewable energy, stringent policy measures, and sustainable urban planning.

Public engagement and international collaboration are crucial. Achieving the ambitious goal of approximately 860 terawatts of carbon-free energy production by 2100 (Figure 19) requires infrastructure development, supportive policies, energy efficiency improvements, and public awareness campaigns (Lan *et al.*, 2021). These actions extend beyond emissions reduction, encompassing improved air quality, enhanced energy security, and economic opportunities for India's future. Globally, consistent GDP-PC growth initially contributed to a decline in both EI and CO<sub>2</sub>-EI, resulting in slow growth of CO<sub>2</sub>-emi until 2000. However, post-2000, there was a deceleration in the reduction of EI and CO<sub>2</sub>-EI, likely attributed to the increasing global population and heightened energy consumption demands. This slowdown, combined with sluggish global GDP-PC growth, resulted in a significant and rapid increase in CO<sub>2</sub>-emi projections extending to 2100. The acceleration in CO<sub>2</sub>-emi growth from 2000 onwards is primarily driven by slower global economic expansion, rapid population growth, increased dependence on fossil fuels, and heightened energy demand across various sectors, as highlighted by ISAMpCO<sub>2</sub> forecasts.

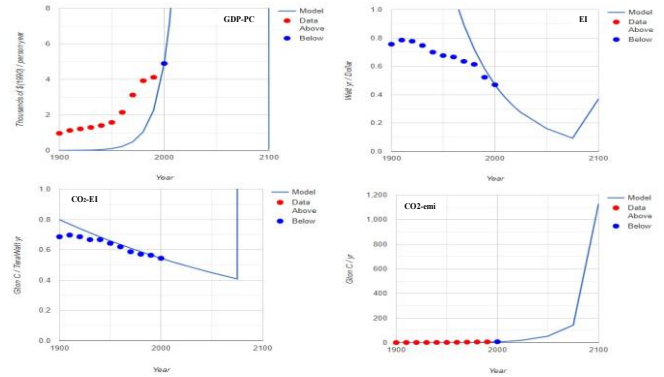


Figure 18: Future Projections of selected variables for India

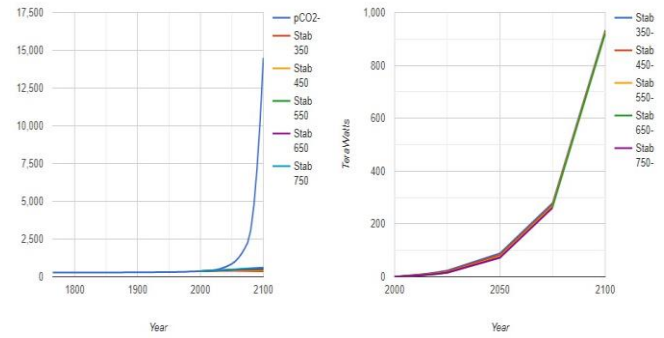


Figure 19: Forecasts for ISAMpCO<sub>2</sub> and Carbon-free energy requirement for India

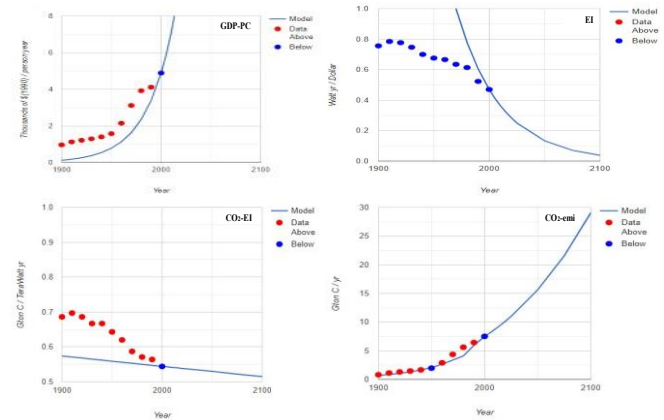


Figure 20: Future Projections of selected variables at global level

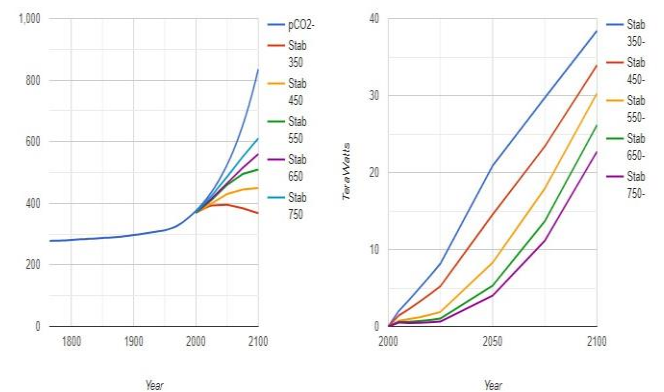


Figure 21: Forecasts for ISAMpCO<sub>2</sub> and Carbon-free energy requirement at global level

To stabilise CO<sub>2</sub> concentrations at 350 ppm by 2100, a monumental shift towards carbon-free energy production is imperative (Figure 21). This shift involves renewables, nuclear power, and potentially carbon capture and storage technologies. It demands a rapid energy transition, supportive policies, global collaboration, energy efficiency

enhancements, and public awareness. These actions are central to mitigating the devastating impacts of climate change and securing a sustainable future for our planet (Friedlingstein *et al.*, 2022).

#### 4.3. Descriptive statistics

The statistical comparison between India and the rest of the world reveals notable differences in key indicators (Table 1). India exhibits a lower GDP-PC but higher EI and CO<sub>2</sub>-EI compared to the world average, indicating that its economic activities produce more CO<sub>2</sub>-emi per unit of output. However, India's mean CO<sub>2</sub>-emis are slightly lower than the world average. The world exhibits lower variability in these

indicators (except EI), as indicated by the higher coefficient of variation (CV) values. These distinctions are influenced by population distribution, economic development stage, and energy consumption patterns. In contrast, the world average reflects more diverse economic and environmental circumstances across various countries, resulting in lower variability in the selected indicators. Notably, both datasets have negative skewness in CO<sub>2</sub>-EI and CO<sub>2</sub>-emi, suggesting a tendency towards lower values. Finally, the kurtosis values suggest that the distributions in both datasets are slightly leptokurtic, implying that they have heavier tails and are less normal in distribution compared with a standard normal curve.

**Table 1: Summary statistics of the selected variables**

Item	Population	GDP-PC	EI	CO <sub>2</sub> -EI	CO <sub>2</sub> -emi
<b>All-India (log values)</b>					
Mean	1.1632	2.9120	3.1451	3.1009	9.0876
SD	0.1603	0.2975	0.1088	0.0380	0.2491
CV	0.1378	0.1022	0.0346	0.0122	0.0274
Min	0.8890	2.4920	2.9790	3.0210	8.6370
Max	1.4080	3.3570	3.2870	3.1760	9.4260
Skewness	-0.1202	0.0323	-0.0208	-0.0175	-0.2579
Kurtosis	1.7752	1.4161	1.4130	2.5997	1.7718
<b>World (log values)</b>					
Mean	6.6585	3.8726	0.0001	1.9705	9.4613
SD	0.7647	0.1472	0.00001	0.0069	0.0910
CV	0.1148	0.0380	0.2406	0.0035	0.0096
Min	5.4060	3.6470	0.0000	1.9540	9.2680
Max	7.9090	4.0840	0.0001	1.9800	9.5750
Skewness	0.0277	-0.0924	0.1164	-0.9226	-0.3606
Kurtosis	1.7864	1.3619	1.2869	3.0587	1.9089

#### 4.4. Correlation matrix

Before applying ridge regression, the findings from correlation analysis at both at all-India and global levels reveal distinct patterns. At the all-India level (Table 2), a positive correlation between population and GDP-PC indicates that as population grows, GDP-PC tends to increase. Concurrently, population varies inversely with EI and moderately so with CO<sub>2</sub>-EI, indicating that increased population correlates with decreased EI and, to some extent, reduced CO<sub>2</sub>-EI. Moreover, a strong negative correlation exists between GDP-PC and EI in the Indian context, whereas

the association between GDP-PC and CO<sub>2</sub>-EI is weaker. On the global stage (Table 3), these correlations are more pronounced. Here, strong negative correlations between GDP-PC and EI and between EI and CO<sub>2</sub>-EI, underscore that as global prosperity increases, energy efficiency tends to improve, leading to reduced CO<sub>2</sub>-EI. There is a weak correlation between GDP-PC and CO<sub>2</sub>-EI. Furthermore, CO<sub>2</sub>-emi showed a strong positive correlation with population and GDP-PC, but a negative correlation with EI and CO<sub>2</sub>-EI both at India and global levels, emphasising intricate relationships among these factors (Zhao *et al.*, 2022).

**Table 2: Correlation matrix among selected variables at the Indian level**

	Population	logGDP-PC	logEI	logCO <sub>2</sub> -EI
logGDP-PC	0.9826**			
logEI	-0.7958**	-0.8636**		
logCO <sub>2</sub> -EI	-0.3770*	-0.3340	-0.1358	
logCO <sub>2</sub> -emi	0.9961**	0.9766**	-0.7968**	-0.3593*

Note: \*\* & \* - Significant at 1% and 5%, levels respectively

**Table 3: Correlation matrix among selected variables at the global level**

	Population	logGDP-PC	logEI	logCO <sub>2</sub> -EI
logGDP-PC	0.9662**			
logEI	-0.9498**	-0.9964**		
logCO <sub>2</sub> -EI	-0.3860*	-0.1999	0.1725	
logCO <sub>2</sub> -emi	0.9824**	0.9776**	-0.9626**	-0.3756*

Note: \*\* & \* - Significant at 1% and 5%, levels respectively

#### 4.5. Unit Root Test

The results of the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests (Table 4) for the selected variables indicate that all variables for both India and the world are non-stationary at the level but become stationary

after first differencing, denoted as I (1). This consistency across both ADF and PP tests underscores that differencing the series once is sufficient to achieve stationarity, which is essential for conducting reliable OLS regression analysis.

**Table 4: Results of ADF and PP unit root tests for selected variables (probability values)**

Variables	ADF test statistics		PP test statistics		Order of Integration
	Level	First Difference	Level	First Difference	
<b>India</b>					
Real GNP	0.9804	0.0167*	0.9794	0.0157*	I (1)
CO <sub>2</sub> -emi	0.4041	0.0030**	0.4347	0.0000**	I (1)
MaxT	0.0696	0.0000**	0.0953	0.0000**	I (1)
MinT	0.6008	0.0000**	0.3626	0.0000**	I (1)
FL	0.8635	0.0000**	0.4406	0.0005**	I (1)
RF	0.4154	0.0026**	0.4736	0.0224*	I (1)
GFCF	0.9696	0.0051**	0.5020	0.0158*	I (1)
<b>World</b>					
Real GNP	1.0000	0.0019**	0.7518	0.0049**	I (1)
CO <sub>2</sub> -emi	0.5330	0.0054**	0.5952	0.0041**	I (1)
MaxT	0.2221	0.0120*	0.2098	0.0128*	I (1)
MinT	0.7505	0.0016**	0.4969	0.0049**	I (1)
FL	1.0000	0.0014**	0.5761	0.0148*	I (1)
RF	0.5573	0.0034**	0.6073	0.0060**	I (1)
GFCF	0.5385	0.0125*	0.6562	0.0455*	I (1)

Note: \*\* & \* denote significance at 1 and 5 per cent levels

Raw Data Source: [www.fao.org](http://www.fao.org)

#### 4.6. OLS estimation results

In both the all-India and global contexts, the OLS estimation results for CO<sub>2</sub>-emi reveal significant findings (Tables 5 and 6). There is a significant positive relationship between population and CO<sub>2</sub>-emi, indicating that as population increases, CO<sub>2</sub>-emi tends to rise, which holds true for both India and the world. However, other critical determinants, including GDP-PC, EI, and CO<sub>2</sub>-EI, did not exhibit a statistically significant association with CO<sub>2</sub>-emi in either case. Moreover, both India and the global dataset share the challenge of strong multicollinearity among population, GDP-PC, and EI, potentially undermining the models'

stability and interpretability (Xilong *et al.*, 2015; Chekouri & Benbouziane, 2020). Additionally, the presence of positive autocorrelation in the residuals, as indicated by the Durbin-Watson statistic, raises concerns about the models' assumptions in both instances. Consequently, these limitations emphasise the application of Ridge regression to address multicollinearity and autocorrelation issues and gain a more robust understanding of the determinants of CO<sub>2</sub>-emi, both at the national and global levels.

**Table 5: OLS estimation results at the Indian level**

Parameter	Estimate	SE	Lower Limit	Upper Limit	VIF
Constant	7.996	2.038	3.806	12.185	--
Population	1.783**	0.210	1.351	2.214	67.072
logGDP-PC	-0.170	0.187	-0.553	0.214	182.503
logEI	-0.137	0.243	-0.636	0.363	41.353
logCO <sub>2</sub> -EI	-0.018	0.320	-0.676	0.640	8.742
R <sup>2</sup>	0.9932				
Adjusted R <sup>2</sup>	0.9918**				
Durbin-Watson stat	1.0196**				

Note: \*\* - Significant at the 1% level

**Table 6: OLS estimation results at the global level**

Parameter	Estimate	SE	Lower Limit	Upper Limit	VIF
Constant	2.021	0.911	0.148	3.893	
Population	0.073**	0.010	0.051	0.094	27.180
logGDP-PC	0.857	0.685	0.476	1.237	316.374
logEI	0.572	0.314	0.275	0.869	214.794
logCO <sub>2</sub> -EI	-1.659	1.259	1.127	2.191	1.367
R <sup>2</sup>	0.9927				
Adjusted R <sup>2</sup>	0.9915**				
Durbin-Watson stat	0.5075**				

Note: \*\* - Significant at the 1% level

#### 4.7. Ridge regression estimation results

The ridge trace graphs at both the Indian and global levels (Figures 22 and 23) highlight the impact of ridge regularisation on the Variance Inflation Factors (VIFs) of the independent variables. These graphs demonstrate that as the ridge parameter increases, the VIFs gradually decrease. At the Indian level, when the ridge parameter reaches approximately 0.157, the VIFs drop to zero, indicating effective mitigation of multicollinearity among the independent variables.

Similarly, at the global level, the VIFs reach zero at a ridge parameter of approximately 0.208, signifying a successful reduction of multicollinearity globally. Achieving zero VIFs at specific ridge parameter values signifies the effectiveness of ridge regularisation in enhancing the reliability and interpretability of the model, making it more suitable for analysing and understanding the determinants of CO<sub>2</sub>-emi at different geographical scales (Feng, 2017; Congjun *et al.*, 2023).

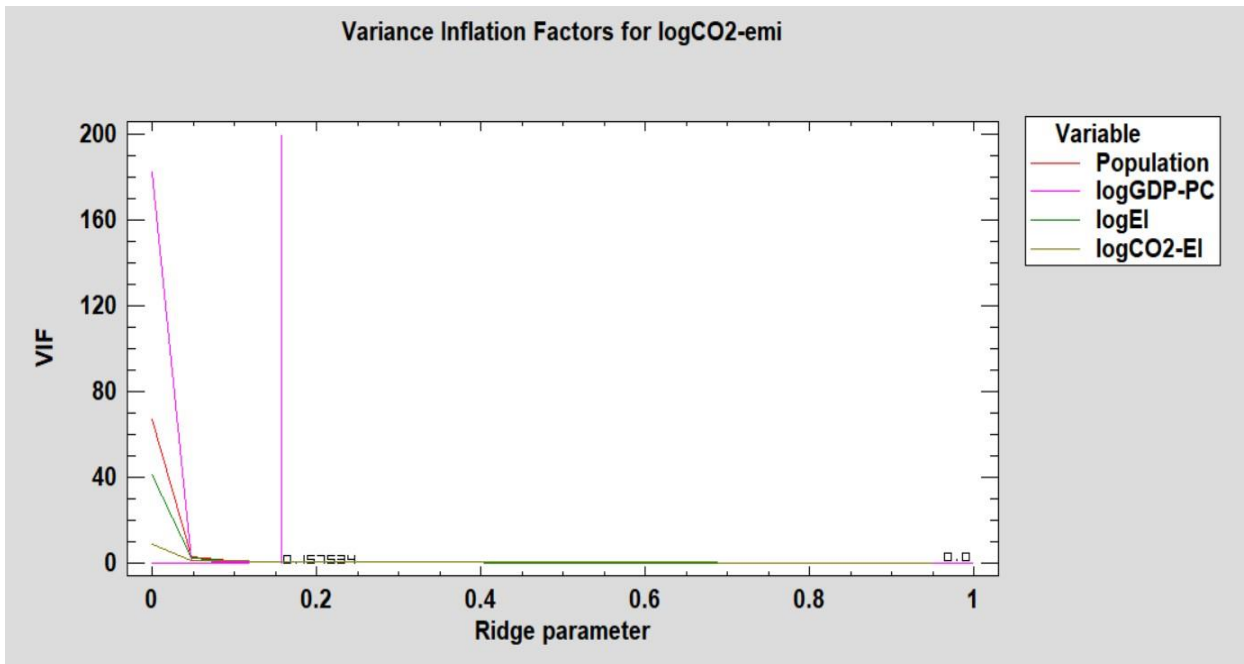


Figure 22: Ridge trace at All-India level

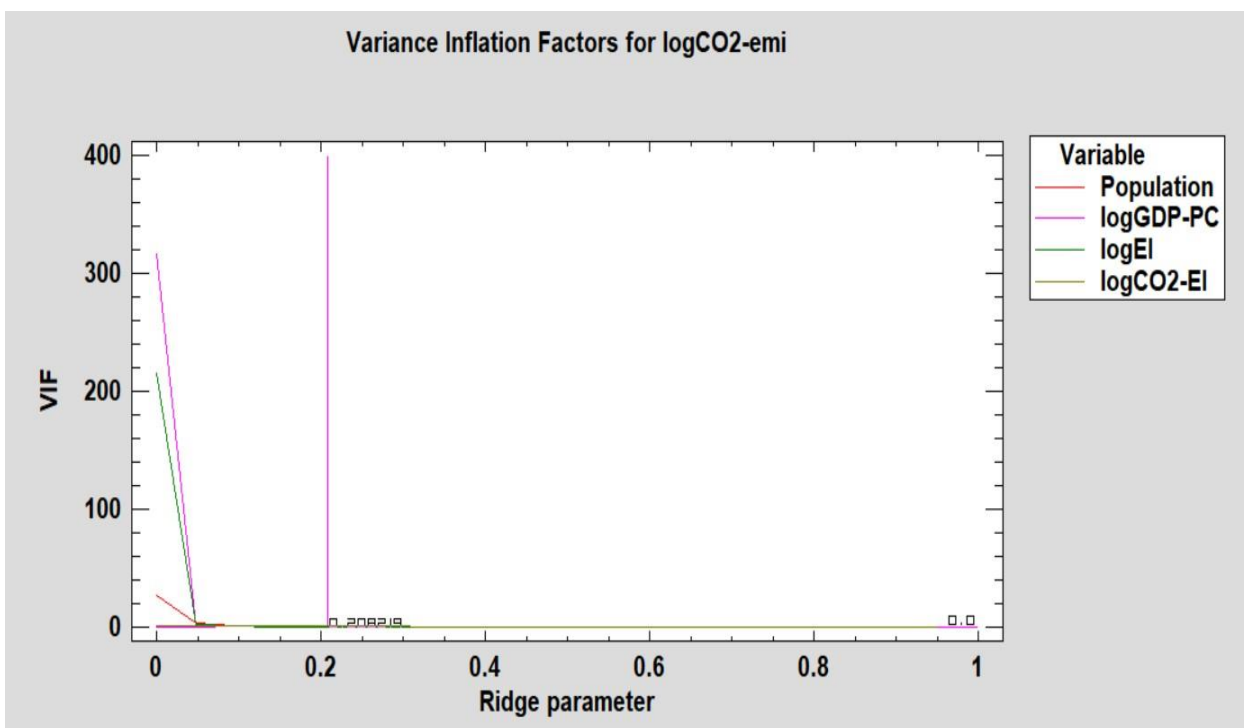


Figure 22: Ridge trace at global level

The ridge regression analysis for CO<sub>2</sub>-emi at both the all-India and global levels, using ridge parameters of 0.157 and 0.208, respectively, provides valuable insights (Tables 7 and 8). Notably, the introduction of ridge regularisation effectively mitigated multicollinearity among the independent variables in both datasets, substantially reducing the VIFs. This reduction in multicollinearity enhances the model's stability and the reliability of coefficient estimates (Lin *et al.*, 2009; Jia *et al.*, 2009; Noorpoor and Kudahi, 2015).

In both India and the global context, the ridge regression results shed light on the key determinants of CO<sub>2</sub>-emi. Notably, a higher population exerted a significant positive influence on CO<sub>2</sub>-emi in both cases, even after addressing multicollinearity issues. This underscores the substantial impact of population growth on emissions, emphasising the need for sustainable population management strategies. Similarly, increased GDP-PC positively affects CO<sub>2</sub>-emi in both India and the rest of the world, emphasising the role of economic prosperity in driving emissions. Furthermore, lower EI and reduced CO<sub>2</sub>-EI are associated with lower CO<sub>2</sub>-emi, highlighting the importance of energy efficiency and the

transition to cleaner energy sources in mitigating emissions. These commonalities between India and the rest of the world emphasise the global nature of these determinants and underscore the need for coordinated efforts at both national and international levels to address the challenges posed by population growth, economic development, and sustainable energy practices towards climate change mitigation.

The adjusted R-squared values of 0.9051 for India and 0.8933 for the world indicate a significant portion of the variance in

CO<sub>2</sub>-emi is explained by the independent variables, while the MAE metrics confirm the models' predictive accuracy. The Durbin-Watson statistics (2.0007 for India and 2.0010 for the world) show no substantial autocorrelation in residuals, affirming error independence. These findings reinforce the robustness of ridge regression models in capturing CO<sub>2</sub>-emi determinants, providing a reliable basis for policy and decision-making at both national and global scales (Figures 23 and 24).

**Table 7: Ridge regression estimation results at the Indian level (Ridge Parameter = 0.157)**

Variable	Marginal Effect (B)	Elasticity (Es)	Mean	VIF
Population	0.7254**	0.0929	1.1632	0.710159
GDP-PC	0.2696**	0.0864	2.9120	0.202232
EI	-0.3133**	-0.1084	3.1451	0.774308
CO <sub>2</sub> -EI	-0.5367**	-0.1831	3.1009	0.751581

R<sup>2</sup> = 0.9178

R<sup>2</sup> Adj = 0.9051

MAE = 0.0298

Durbin-Watson statistic = 2.0007

Note: \*\* - Significant at the 1% level

**Table 8: Ridge regression estimation results at the global level (Ridge Parameter = 0.208)**

Variable	Marginal Effect (B)	Elasticity (Es)	Mean	VIF
Population	0.0460**	0.0324	6.6585	0.5422
GDP-PC	0.1849**	0.0757	3.8726	0.1799
EI	-0.1476**	-0.0421	1.9349	0.3093
CO <sub>2</sub> -EI	-0.5309**	-0.1106	1.9705	0.6992

R<sup>2</sup> = 0.9075

R<sup>2</sup> Adj = 0.8933

MAE = 0.0106

Durbin-Watson statistic = 2.0010

Note: \*\* - Significant at the 1% level

#### 4.8. Relative degree of contribution to CO<sub>2</sub>-emi

In both India and the global context (Tables 9 and 10), the analysis highlights significant factors impacting CO<sub>2</sub>-emi, each with distinct implications. Population growth emerges as a pivotal factor, and its influence on emissions is evident in both cases. In India, a 1% increase in the annual population growth rate corresponds to a 3.0031% rise in emissions. This emphasises the urgent need for sustainable urban planning and clean energy solutions to mitigate CO<sub>2</sub>-emi. Similarly, at the global level, a 1% increase in the annual population growth rate results in a 0.9826% increase in global CO<sub>2</sub>-emi, highlighting the imperative of managing population growth sustainably (Lin, 2017; Usman & Hammar, 2021). Economic development, represented by GDP-PC, significantly affects

emissions in both contexts, underscoring the challenge of balancing economic growth with emissions reduction goals. EI plays a pivotal role in emissions reduction, with a 1% increase in its annual growth rate leading to decreased emissions in both India and the world. Lastly, although the impact of CO<sub>2</sub>-EI is relatively smaller, it highlights the importance of transitioning towards cleaner energy sources in both cases. These findings emphasise the multifaceted nature of emissions determinants and consequent holistic approaches to integrate population control, economic development, energy efficiency, and clean energy adoption to effectively address emissions challenges, whether on a national or global scale.

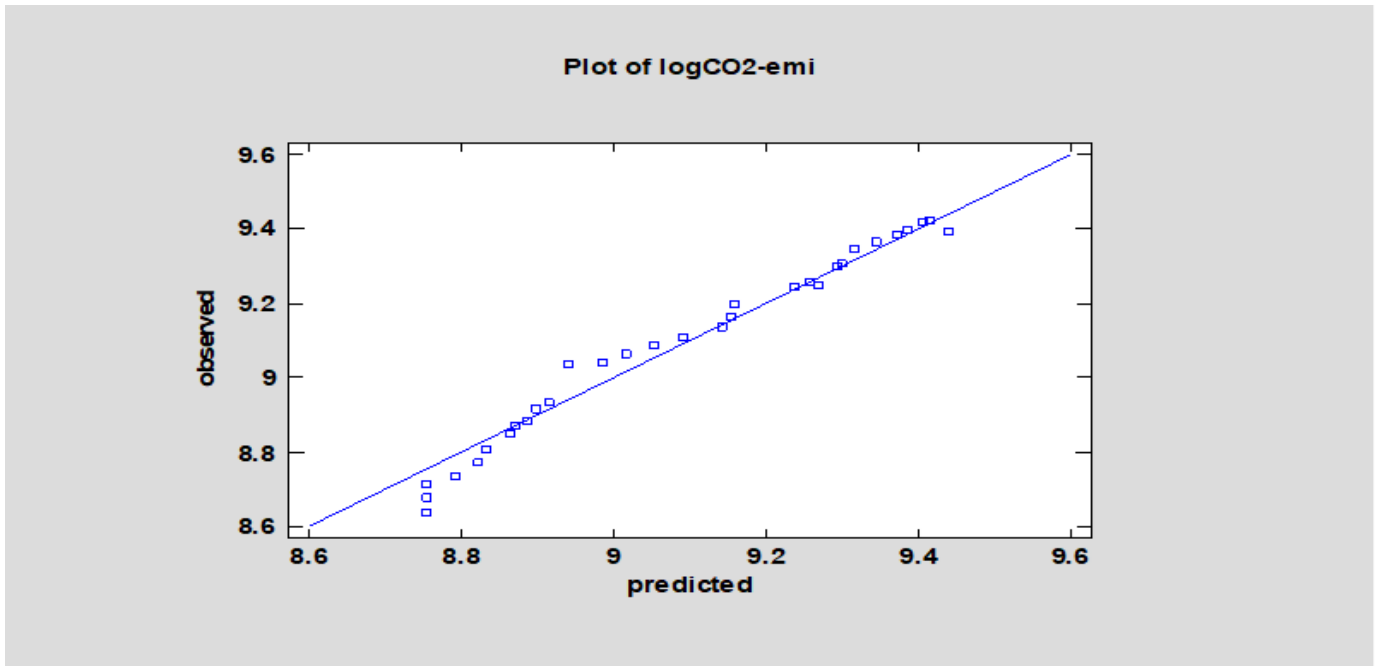


Figure 23: Goodness of Fit of Ridge regression model at All -India level

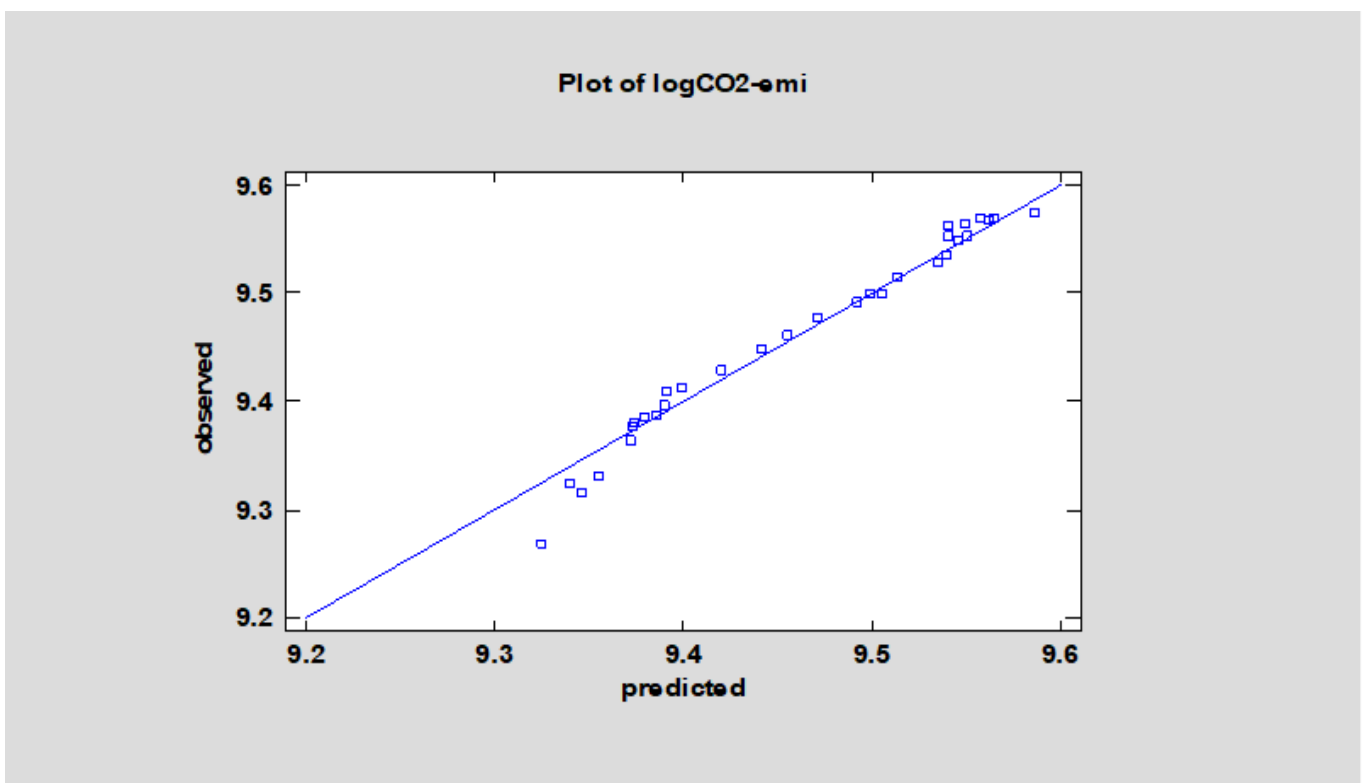


Figure 24: Goodness of Fit of Ridge regression model at global level

Table 9: Relative degree of contribution of selected variables to CO<sub>2</sub>-emi at All-India level

Variables	CAGR (%)	Regression Coeff.	Effect on Change	Contribution Degree (%)
Population	4.1400	0.7254	3.0031	50.4211
GDP-PC	7.6900	0.2696	2.0732	34.8081
EI	-2.1400	-0.3133	0.6705	11.2566

CO <sub>2</sub> -EI	-0.3900	-0.5367	0.2093	3.5142
---------------------	---------	---------	--------	--------

**Table 10: Relative degree of contribution of selected variables to CO<sub>2</sub>-emi at global level**

Variables	CAGR (%)	Regression Coeff.	Effect on Change	Contribution Degree (%)
Population	21.3600	0.0460	0.9826	47.7054
GDP-PC	3.6700	0.1849	0.6786	32.9467
EI	-2.5200	-0.1476	0.3719	18.0591
CO <sub>2</sub> -EI	-0.0500	-0.5309	0.0265	1.2888

**4.9. ARDL Bound Test**

The ARDL Bound Test serves as a crucial tool for examining potential cointegration among the variables under consideration both at the all-India level and the global level. As depicted in Table 6, this test encompasses both the F-bounds test and the t-bounds test, aiming to scrutinize the existence of a long-run relationship among the variables. The calculated F and t-statistics surpass the upper bounds of I (1) critical values at the 1% and 5% significance levels, leading

to the rejection of the null hypothesis stating "no cointegration among variables in the long run." These findings indicate that there is a long-term cointegration relationship between CO<sub>2</sub>-emi and the selected variables, both at the all-India level and globally. Consequently, the consistency with the existing body of literature enhances the credibility of the findings and underscores the robustness of the results.

**Table 11: ARDL Bound Test Results**

ARDL Long Run Form and Bounds Test

Dependent Variable: D(CO<sub>2</sub>-emi)

Selected Model: ARDL (4, 3, 4, 4, 1, 4, 4)

F-Bounds Test All-India level			Ho: No levels relationship	
Test Statistic	Value	Signif.	I(0)	I(1)
F-statistic K	15.113 6	10% 5% 2.5% 1%	Asymptotic: n=1000	
			2.12	3.23
			2.45	3.61
			2.75	3.99
			3.15	4.43
			Finite Sample: n=50	
			2.309	3.507
			2.726	4.057
			3.656	5.331
			Finite Sample: n=45	
			2.327	3.541
			2.764	4.123
3.79	5.411			
t-statistic	5.999	10% 5% 2.5% 1%	-2.57	-3.66
			-2.86	-3.99
			-3.13	-4.26
			-3.43	-4.61
<b>Global level</b>				
F-statistic K	10.973 4	10% 5% 2.5% 1%	Asymptotic: n=1000	
			2.45	3.52
			2.86	4.01
			3.25	4.49
			3.74	5.06
			Finite Sample: n=35	
			2.696	3.898
			3.276	4.63
			4.59	6.368
			Finite Sample: n=30	



		10%	2.752	3.994
t-statistic	4.818	10%	-2.57	-3.66
		5%	-2.86	-3.99
		2.5%	-3.13	-4.26
		1%	-3.43	-4.6

As corroborated by the ARDL Bounds test, an ECM-Long Run Test was conducted to establish a long-run association between the variables, with the results presented in Table 12. At both the all-India and global levels, the coefficients and standard errors reveal significant long-run relationships. For instance, the coefficient for CO<sub>2</sub>-emi lagged by one period (CO<sub>2</sub> emi(-1)) is significantly negative for both levels, indicating a strong long-run adjustment mechanism where deviations from equilibrium levels are corrected over time. Population (POP(-1)) and GDP per capita (GDP\_PC(-1)) show significant positive and negative associations, respectively, at the all-India level, suggesting that while population growth contributes to increased CO<sub>2</sub>-emi, higher GDP per capita may correlate with investments in cleaner technologies and more efficient practices. Conversely, at the global level, the negative impact of population on CO<sub>2</sub>-emi might reflect the effectiveness of global initiatives aimed at sustainable development, while the positive association with GDP per capita could indicate higher consumption and industrial activities in wealthier countries. (EI(-1)) exhibits a significant positive impact on CO<sub>2</sub>-emi in India, likely due to

the country's ongoing industrialization and reliance on fossil fuels. In contrast, the substantial negative impact globally reflects the broader adoption of energy-efficient technologies and cleaner energy sources in many parts of the world, driven by stringent environmental regulations and international climate agreements. The dynamic terms, such as D(CO<sub>2</sub> emi(-1)) and D(CO<sub>2</sub> emi(-2)), along with other differenced variables, further underscore the complex interactions and adjustment dynamics in the short run. These findings highlight significant regional differences in how these variables interact and adjust over time, reinforcing the importance of tailored policy interventions for emissions control. For India, policies might focus on accelerating the transition to renewable energy and improving energy efficiency in industrial processes, while globally, continued efforts to enhance sustainable development and enforce environmental regulations are crucial. This divergence underscores the need for context-specific strategies to effectively manage CO<sub>2</sub>-emi and mitigate climate change impacts.

**Table 12: ECM-Long Run Test**

Dependent Variable: D(CO<sub>2</sub>-emi)

Selected Model: ARDL (4, 4, 4, 4, 4)

Case 3: Unrestricted Constant and No Trend

Variables	All-India level		Global level	
	Coefficient	Std. Error	Coefficient	Std. Error
C	0.601**	0.185	-5.043**	1.391
CO <sub>2</sub> _emi(-1)*	-2.055**	0.114	-1.038**	0.270
POP(-1)	3.487**	0.910	-0.036*	0.018
GDP_PC(-1)	0.545**	0.100	-1.323**	0.171
EI(-1)	1.907**	0.689	-7.921**	1.259
CO <sub>2</sub> _EI(-1)	2.038*	0.841	0.334**	0.096
D(CO <sub>2</sub> _emi(-1))	0.364**	0.060	-1.675**	0.117
D(CO <sub>2</sub> _emi(-2))	0.732**	0.267	-0.777**	0.354
D(CO <sub>2</sub> _emi(-3))	0.909**	0.142	-0.830***	0.232
D(POP)	13.051*	5.244	-2.161**	0.160
D(POP(-1))	0.405	27.702	-0.363**	0.067
D(POP(-2))	-42.329	24.504	3.225	2.399
D(POP(-3))	27.057	23.614	4.057	4.949
D(GDP_PC)	1.686**	0.431	0.770*	0.329
D(GDP_PC(-1))	1.712**	0.386	1.558**	0.357
D(GDP_PC(-2))	0.490	0.359	0.970	1.128
D(GDP_PC(-3))	0.731**	0.309	0.798**	0.292
D(EI)	1.926**	0.515	1.560**	0.297
D(EI(-1))	0.299**	0.059	0.392**	0.114
D(EI(-2))	-0.297	0.383	0.253	0.365
D(EI(-3))	0.321	0.286	0.485	0.350

D(CO <sub>2</sub> _EI)	0.766*	0.318	1.023**	0.402
D(CO <sub>2</sub> _EI(-1))	-0.781	0.540	0.431**	0.144
D(CO <sub>2</sub> _EI(-2))	-0.544	0.425	0.286**	0.086
D(CO <sub>2</sub> _EI(-3))	0.557	0.441	0.546	1.105

Note: \* p-value incompatible with t-Bounds distribution.

## 5. Summary and conclusion

This study delves into the significance of Kaya's identity in understanding and addressing CO<sub>2</sub>-emi, both nationally and globally. Kaya's identity, developed by Japanese energy economist Yoichi Kaya, provides a mathematical framework that breaks down total CO<sub>2</sub>-emi (or environmental impact, I) into four fundamental components: human population, GDP-PC, EI, and CO<sub>2</sub>-EI. To conduct this analysis, relevant data from FAOSTAT spanning 1991-2021 was utilised, encompassing both the all-India level and the global scale. In the pursuit of comprehending the intricate interplay of factors influencing CO<sub>2</sub>-emi researchers frequently resort to sophisticated statistical models. One such model, the STIRPAT model, proves invaluable in revealing the connections between selected independent variables and the, CO<sub>2</sub>-emi. However, the application of the STIRPAT model via OLS regression to real-world data encountered multicollinearity issues, which potentially endangered the reliability of the coefficient estimates. To address this challenge, Ridge regression was employed as an alternative approach, enhancing the robustness and accuracy of the analysis.

The analysis of trends in the selected variables revealed critical insights into the complex dynamics of CO<sub>2</sub>-emi in both India and the global context. Population growth, which increased by 4.14% in India and 21.36% globally between 1991 and 2021, emerged as a significant driver of CO<sub>2</sub>-emi. A larger population drives up resource demand, energy consumption, and emissions, posing challenges to resource sustainability and air quality. Rapid population growth in India intensifies energy demand and emissions, which are primarily reliant on fossil fuels. GDP-PC, growing at a rate of 7.69% in India, was found to be higher than the global average of 3.67% and is linked to increased emissions. India's youthful population, economic reforms, and service sector dominance contribute to this growth. On a global scale, variations in economic growth among countries influence emissions patterns, with developed economies exhibiting slower growth. EI trends indicate the importance of energy efficiency in emissions reduction. India's shift towards a services-oriented economy, investments in energy-efficient technologies, and renewable energy adoption have lowered EI. Globally, stringent environmental regulations and technological advancements have led to a reduction in EI. CO<sub>2</sub>-EI is crucial for emissions reduction. India's decrease in CO<sub>2</sub>-EI is attributed to renewable energy expansion, cleaner technologies, and improved energy efficiency. Globally, the adoption of renewables and energy-efficient practices has led to a decrease in CO<sub>2</sub>-EI. CO<sub>2</sub>-emi increased by 6.46% in India and 2.29% globally during the study period. India's rapid economic growth, reliance on fossil fuels, and infrastructure development drove emissions. Determinants of CO<sub>2</sub>-emi were analysed. Population growth and GDP-PC exhibited positive associations with emissions in both India and the global dataset. Lower EI and CO<sub>2</sub>-EI were linked to reduced

emissions, emphasising energy efficiency and clean energy adoption. Ridge regression effectively mitigated multicollinearity and provided robust results. Population growth and GDP-PC remained significant factors influencing emissions in both India and the global dataset.

The ISAMpCO<sub>2</sub> forecasts revealed that sustained GDP-PC growth in India led to declining trends in both EI and CO<sub>2</sub>-EI, resulting in a gradual increase in CO<sub>2</sub>-emi until 2080. However, after this point, possibly due to population growth and increased energy demands, the capacity to offset rising EI and CO<sub>2</sub>-EI waned, leading to a rapid surge in CO<sub>2</sub>-emi from 2080 onwards. Globally, consistent GDP-PC growth initially contributed to a reduction in EI and CO<sub>2</sub>-EI, resulting in slow CO<sub>2</sub>-emi growth until 2000. However, post-2000, a slowdown in the decrease of EI and CO<sub>2</sub>-EI, driven by population growth and heightened energy consumption, led to a sharp and swift increase in CO<sub>2</sub>-emi projections up to 2100, influenced by sluggish global economic expansion and greater reliance on fossil fuels.

The study underscores the profound influence of population growth on CO<sub>2</sub>-emi, both in India and globally, emphasising the urgency of implementing sustainable population management strategies. Moreover, it accentuates the intricate interplay between economic advancement, as gauged by GDP-PC, and emissions, emphasising the necessity of achieving a nuanced equilibrium between economic prosperity and the pursuit of emissions reduction goals. This study also emphasises the critical role of energy-efficient technologies and the transition to cleaner energy sources as essential strategies for mitigating emissions.

Findings also showed a long-term cointegration relationship between CO<sub>2</sub>-emi and the selected variables at both the all-India and global levels. The significantly negative coefficient for CO<sub>2</sub>-emi lagged by one period (CO<sub>2</sub>\_emi(-1)) suggests a strong long-run adjustment mechanism. Population (POP(-1)) and GDP-PC (GDP\_PC(-1)) show significant positive and negative associations, respectively, at the all-India level, while globally, these relationships are reversed, highlighting regional differences. Energy intensity (EI(-1)) shows a significant positive impact on CO<sub>2</sub>-emi in India, likely due to industrialization and fossil fuel reliance, while globally, the negative impact reflects a broader adoption of energy-efficient technologies driven by stringent environmental regulations.

Effectively mitigating CO<sub>2</sub>-emi in India and globally necessitates a comprehensive strategy encompassing green economy regulations to stimulate sustainable practices, promote the development and adoption of eco-friendly technologies across industries, address economic inequality through income redistribution policies and opportunities for marginalised communities, expedite the transition to green energy sources such as solar, wind, and geothermal power, and encourage family planning measures to indirectly curb population growth (McGee & Greiner, 2018;

Kusumawardani & Dewi, 2020; Yang *et al.*, 2021). Alongside these initiatives, fostering public awareness, fostering international cooperation, and implementing robust monitoring systems are pivotal elements of this holistic approach, collectively aimed at reducing carbon footprints and contributing significantly to global climate change mitigation efforts.

Future research avenues should include assessing the impact of specific policy interventions, exploring newer technologies such as carbon capture and storage, understanding the influence of consumer behaviour on emissions, analysing regional disparities within countries, and developing long-term scenarios for emissions trends. In conclusion, this study serves as a comprehensive guide to understanding and addressing CO<sub>2</sub>-emi, offering crucial insights for policymakers, stakeholders, and researchers.

#### 6. Data Availability

Data for this study are available upon request.

#### 7. Funding

No financial assistance was received for the preparation of this manuscript.

#### 8. Declaration of interest

The authors declare no conflict of interest.

#### Reference

- Adewale F. L., Matthew O. O., Joshua O. O., & Clement A. O., (2019). The Impacts of Population Change and Economic Growth on Carbon Emissions in Nigeria, *Iranian Economic Review*, 23(3), 715-731
- Ahmad M., Ali A. B., & Rahmatullah M. (2020). Impact of Population and Economic Growth on CO<sub>2</sub> Emissions (Case of Afghanistan), *Journal of Emerging Technologies and Innovative Research*, 7(10), 368-378
- Andreas O. (2013). Long-Term Kaya-Identity Analysis and Prerequisites of a Sustainable and Green Economic Growth in a 2°C World, ISPSW Strategy Series: Focus on Defense and International Security, (236). [https://www.files.ethz.ch/isn/167156/236\\_Oberheiman](https://www.files.ethz.ch/isn/167156/236_Oberheiman)
- Anqing, S. (2001). Population Growth and Global Carbon Dioxide Emissions, Paper presented at IUSSP Conference in Brazil/session-s09, Development Research Group, The World Bank
- Beşer M.K., & Beşer B. H. (2013). The relationship between energy consumption, CO<sub>2</sub> Emissions and GDP per capita: A revisit of the evidence from Turkey, *Alphanumeric Journal*, 5(3), 353-368. <http://dx.doi.org/10.17093/alphanumeric.353957>
- Bismark A., & Li Y.(2018). Analyzing the Impact of GDP on CO<sub>2</sub> Emissions and Forecasting Africa's Total CO<sub>2</sub> Emissions with Non-Assumption Driven Bidirectional Long Short-Term Memory, *Sustainability*, 10,(9), 1-23, 3110. <https://doi:10.3390/su10093110>
- Casey G., & Oded G. (2016). Population Growth and Carbon Emissions, National Bureau of Economic Research, Working Paper 22885, 1-15. <https://doi.org/10.3386/w22885>.
- Chandrima S., &Kakali M., (2016). Impact of Population on Carbon Emission: Lessons from India, *Asia-Pacific Development Journal*, 23(1), 105-132. <https://doi.10.18356/b4c7cba0-en>
- Chekouri S., & Benbouziane M., (2020). Examining the driving factors of CO<sub>2</sub> Emissions using the STIRPAT model: the case of Algeria, *International Journal of Sustainable Energy*, 39(10), 927–940 .doi:<https://doi.org/10.1080/14786451.2020.1770758>.
- Congjun R., Qifan H., Lin C., Mark G., & Zhuo H., (2023). Forecasting the carbon emissions in Hubei Province under the background of carbon neutrality: a novel STIRPAT extended model with ridge regression and scenario analysis, *Environmental Science and Pollution Research*, 30:57460–57480, <https://doi.org/10.1007/s11356-023-26599-w>
- Crippa M., Guizzardi D., Banja M., Solazzo E., Muntean M., Schaaf E., Pagani F., Monforti-Ferrario F., Olivier, J.G.J., Quadrelli, R., Riskez Martin, A., Taghavi-Moharamli, P., Grassi, G., Rossi, S., Oom, D., Branco, A., San-Miguel, J., & Vignati, E. (2022). CO<sub>2</sub> Emissions of all world countries” – JRC/IEA/PBL 2022 Report, Publications Office of the European Union, Luxembourg, doi:10.2760/07904, JRC130363
- Cui, E., Ren, L., & Sun, H. (2017). Analysis on the Regional Difference and Impact Factors of CO<sub>2</sub> Emissions in China, *Environmental Progress Sustainable Energy*, 36 (5), 1282–1289. doi:10.1002/ep.12590
- Danish, R. U, & Salah-Ud-Din, K. (2020). Relationship between energy intensity and CO<sub>2</sub> Emissions: Does economic policy matter?, *Sustainable Development*, 28(5), 1457-1464. <https://doi.org/10.1002/sd.2098>
- Dawit, W. M., & Zerayehu, S. E., (2018). The Driving Forces of CO<sub>2</sub> Emissions and its Responsiveness in Ethiopia: An Integrated Analysis Using Vector Error Correction Model, *Journal of Sustainable Development in Africa*, 20(3), ISSN: 1520-5509
- Dietz, T., & Rosa, E. A., (1997). Effects of population and affluence on CO<sub>2</sub> Emissions, *Proc. Natl. Acad. Sci., USA* 94: 175-179.
- Dolf, G., Francisco, B., Deger S., Morgan, D. B., Nicholas, W., & Ricardo, G., (2019). The role of renewable energy in the global energy transformation, *Energy Strategy Reviews*, 24, 38-50, ISSN 2211-467X, <https://doi.org/10.1016/j.esr.2019.01.006>.
- Dong, K., Dong, X., Dong, C., (2019). Determinants of the Global and Regional CO<sub>2</sub> Emissions: What Causes what and where?, *Applied Economics*, 51 (46), 5031–5044. doi:10.1080/00036846.2019.1606410
- Du, L., Wei, C., & Cai S. (2012). Economic Development and Carbon Dioxide Emissions in China: Provincial Panel Data Analysis, *China Economic Review*, 23 (2), 371–384. doi:10.1016/j.chieco.2012.02.004
- Ehrlich, P. R., & Holdren, J. P. (1971). Impact of Population Growth. Science, *American Association for the*

- Advancement of Science*, 171 (3977): 1212-1217. Bibcode: 1971Sci...171.1212E. doi:10.1126/science.171.3977.1212. JSTOR 1731166. PMID 5545198.
- Erum, R., & Shazia, R., (2022). Modeling the nexus between carbon emissions, urbanization, population growth, energy consumption, and economic development in Asia: Evidence from grey relational analysis, *Energy Reports*, 8, 5430-5442, ISSN 2352-4847, <https://doi.org/10.1016/j.egy.2022.03.179>.
- Feng, S.M., (2017). The Driving Factor Analysis of China's CO<sub>2</sub>-Emissions Based on the STIRPAT Model, *Open Journal of Social Sciences*, 5, 49-58, <https://doi.org/10.4236/jss.2017.55004>
- Friedlingstein, P., O'Sullivan, M., Jones, M. W., Andrew, R. M., Gregor, L., Hauck, J., Le Quééré, C., Luijkx, I. T., Olsen, A., Peters, G. P., Peters, W., Pongratz, J., Schwingshackl, C., Sitch, S., Canadell, J. G., Ciais, P., Jackson, R. B., Alin, S. R., Alkama, R., ... & Zheng, B.,(2022). Global Carbon Budget, *Earth System Science Data*, 14(11), 4811–4900. <https://doi.org/10.5194/essd-14-4811-2022>
- Giambona, F., Jacono, V. L., & Scuderi, R., (2005). The IPAT model: An empirical evidence, *Convegno Intermedio Della Società Italiana di Statistica (SIS)*, 125-128
- González-Torres M., Pérez-Lombard L., Coronel, J.F. & Maestre, I.R., (2021). Revisiting Kaya Identity to define an Emissions Indicators Pyramid, *Journal of Cleaner Production*, 317, 128-328. <https://doi.org/10.1016/j.jclepro.2021.128328>
- Hoerl, A. E. (1962). Application of Ridge Analysis to Regression Problems, *Chemical Engineering Progress*, 58, 54-59
- Hoerl, A. E., & Kennard, R. W., (1970). Ridge regression: biased estimation for nonorthogonal problems, *Technometrics*, 1970, 12(1), 55–67.
- IPCC (2018), Global Warming of 1.5°C: an IPCC special report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty, p14.
- IPCC (2022). “Summary for Policymakers. in Climate Change 2022: Mitigation of Climate Change. Contribution of Working Group III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [P.R. Shukla, J. Skea, R. Slade, A. Al Khourdajie, R. van Diemen, D. McCollum, M. Pathak, S. Some, P. Vyas, R. Fradera, M. Belkacemi, A. Hasija, G. Lisboa, S. Luz, J. Malley, (eds.)]. Cambridge University Press, Cambridge, UK and New York, NY, USA. doi: 10.1017/9781009157926.001
- Jayanarayanan K., Rony Peter, Ajay S., & Sarath R., (2022). The increasing atmospheric CO<sub>2</sub> over India: Comparison to global trends, *iScience*, 25(8), 104863, ISSN 2589-0042. <https://doi.org/10.1016/j.isci.2022.104863>.
- Jia, J., Deng, H., Duan, J., & Zhao, J., (2009). Analysis of the major drivers of the ecological footprint using the STIRPAT model and the PLS method—A case study in Henan Province, China, *Ecological Economics*, 68(11), 2818–2824. doi:<https://doi.org/10.1016/j.ecolecon.2009.05.012>
- Kaya, Y., & Yokoburi, K., (1997). Environment, energy, and economy: strategies for sustainability. Tokyo: United Nations Univ. Press, ISBN 9280809113.
- Krishnan, R., Sanjay, J., Gnanaseelan, C., Mujumdar, M., Kulkarni, A., & Chakraborty, S. (2020). Assessment of Climate Change over the Indian Region: A Report of the Ministry of Earth Sciences (MoES), Government of India, Springer Singapore. <https://doi.org/10.1007/978-981-15-4327-2>
- Kusumawardani, D., & Dewi, A., (2020). The effect of income inequality on carbon dioxide emissions: A case study, *Heliyon*, 6(8). doi:<https://doi.org/10.1016/j.heliyon.e04772>
- Lan, X., B. D. Hall, G. Dutton, J., Mühle, J. W. Elkins, & Vimont. I. J., (2022). Long-lived greenhouses gases [in *State of the Climate in 2021*, Chapter 2: Global Climate]. *Bulletin of the American Meteorological Society*, 103 (8), S81-S84. <https://doi.org/10.1175/BAMS-D-22-0092.1>.
- Leena S., (1997). Energy and CO<sub>2</sub>-Emissions in India: increasing trends and alarming portents, *Energy Policy*, 25(11), 941-949, ISSN 0301-4215. [https://doi.org/10.1016/S0301-4215\(97\)00090-6](https://doi.org/10.1016/S0301-4215(97)00090-6).
- Li, R., & Jiang, R. (2019). Is carbon emission decline caused by economic decline? Empirical evidence from Russia. *Energy & Environment*, 30(4), 672–684. <https://doi.org/10.1177/0958305X18802786>
- Li S., Siu Y. W., & Zhao G., (2021). Driving Factors of CO<sub>2</sub>-Emissions: Further Study Based on Machine Learning, *Frontiers in Environmental Science*, 9:721517. doi:10.3389/fenvs.2021.721517
- Liddle, B., (2011). Consumption-Driven Environmental Impact and Age Structure Change in OECD Countries. *Demographic Research*, 24, 749–770. doi:<https://doi.org/10.4054/demres.2011.24.30>
- Lin, S., Wang, S., Marinova, D., Zhao, D., & Hong, J., (2017). Impacts of urbanization and real economic development on CO<sub>2</sub> emissions in non-high income countries: Empirical research based on the extended STIRPAT model, *Journal of Cleaner Production*, 166, 952-966
- Luqman, M., Rayner, P.J., & Gurney, K.R., (2023). On the impact of urbanisation on CO<sub>2</sub> emissions. *npj Urban Sustain*, 3, 6. <https://doi.org/10.1038/s42949-023-00084-2>
- Malhi, G.S., Kaur, M., & Kaushik, P., (2021). Impact of Climate Change on Agriculture and Its Mitigation Strategies: A Review, *Sustainability*, 13, 1318. <https://doi.org/10.3390/su13031318>
- Martínez-Zarzoso I., Bengochea-Morancho A., & Morales-Lage, R., (2006). The Impact of Population on CO<sub>2</sub> emissions: Evidence from European Countries, FEEM Working Paper 98, 06. <https://ssrn.com/abstract=902703> or <http://dx.doi.org/10.2139/ssrn.902703>
- McGee, J. A., & Greiner, P. T., (2018). Can Reducing Income Inequality Decouple Economic Growth from CO<sub>2</sub> emissions? *Socius: Sociological Research for a Dynamic World*, 4, 1-11.
- Melisa C., (2022). Determinants of CO<sub>2</sub> Emission Intensity: Manufacturing Firm-Level Evidence in Indonesia, *Journal Perencanaan Pembangunan: The Indonesian*

- Journal of Development Planning*, 4(3), 402 – 419. <https://doi.org/10.36574/jpp.v6i3.296>
- Metz, B., Davidson O., Bosch P., Dave R., & Meyer L. (2007). *Ipcc, 2007: Climate change 2007: Mitigation. Contribution of working group III to the fourth assessment report of the Intergovernmental Panel on Climate Change.*
- Mirza, F. M., Sinha, A., K, Javeria R., Kalugina, O. A., Zafar M. W. (2022). *Impact of Energy Efficiency on CO<sub>2</sub> emissions: Empirical Evidence from Developing Countries, Gondwana Research*, 106, 64-77.
- Mohanty A., & Wadhawan S., (2021). Mapping India's Climate Vulnerability—A District Level Assessment Council on Energy, Environment and Water, <https://www.ceew.in/sites/default/files/ceew-study-on-climatechange-vulnerability-index-and-district-level-risk-assessment.pdf>
- Mohsin M., Abbas Q., Zhang J., Ikram M., & Iqbal, N., (2019). Integrated effect of energy consumption, economic development, and population growth on CO<sub>2</sub> based environmental degradation: A case of transport sector, *Environmental Science and Pollution Research*, 26 (32), 32824–32835. <http://dx.doi.org/10.1007/s11356-019-06372-8>.
- Nathaniel V. D., Rahmat N., & Farizal F., (2022). Review of Indonesia's Residential and Demographic Carbon Emission Using STIRPAT Model, Proceedings of the 7th North American International Conference on Industrial Engineering and Operations Management, Orlando, Florida, USA, June 12-14,
- Nikunj P., & Dhyani M., (2023). The asymmetry effect of industrialization, financial development and globalization on CO<sub>2</sub>-Emissions in India, *International Journal of Thermo fluids*, 20, 100397, ISSN 2666-2027. <https://doi.org/10.1016/j.ijft.2023.100397>.
- Noorpoor, A., & Kudahi, S., (2015). CO<sub>2</sub> emissions from Iran's power sector and analysis of the influencing factors using the stochastic impacts by regression on population, affluence and technology (STIRPAT) model, *Carbon Management*, 6(3), 101-116. doi:10.1080/17583004.2015.1090317
- Parikh J., Ganesh-Kumar A., & Vinay S., (2009). CO<sub>2</sub>-Emissions structure of Indian economy, *Energy*, doi:10.1016/j.energy.2009.02.014
- Rafał K., (2015). Economic growth and CO<sub>2</sub> emissions: the ECM analysis, *Journal of International Studies*, 8(3), 91-98. DOI: 10.14254/2071-8330.2015/8-3/7
- Rahiman R., Yenneti K., & Panda, A., (2019). Making Indian Cities Energy Smart, TERI-UNSW Policy Brief (New Delhi: The Energy and Resources Institute).
- Ratanavaraha V., & Jomnonkwo, S., (2015). Trends in Thailand CO<sub>2</sub>-Emissions in the transportation sector and Policy Mitigation, *Transport Policy*, 41, 136-146.
- Rehman S., Rehman E., Mumtaz A., & Jianglin Z., (2022). A multicriteria decisionmaking approach in exploring the nexus between wind and solar energy generation, economic development, fossil fuel consumption, and CO<sub>2</sub> emissions. *Frontiers in Environmental Science*, 9, 659. <http://dx.doi.org/10.3389/fenvs.2021.819384>.
- Sarvar G., Jeyhun I., Mikayilov, Shahriyar Mukhtarov & Sakit Yagubov (2023). Forecasting 2030 CO<sub>2</sub> reduction targets for Russia as a major emitter using different estimation scenarios, *Journal of Applied Economics*, 26(1), 1-26. DOI: 10.1080/15140326.2022.2146861
- Shah S.A.A., Shah S.Q.A., & Tahir M., (2022). Determinants of CO<sub>2</sub> emissions: exploring the unexplored in low-income countries, *Environmental Science and Pollution Research*, 29, 48276–48284. <https://doi.org/10.1007/s11356-022-19319-3>
- Shahbaz M., Chaudhary A., & Ozturk, I., (2017). Does urbanization cause increasing energy demand in Pakistan? Empirical evidence from STIRPAT model, *Energy*, 122, 83-93.
- Sunila, S. S., (2011). Determinants of carbon dioxide emissions: Empirical evidence from 69 countries, *Applied Energy*, 88(1), 376-382. <https://doi.org/10.1016/j.apenergy.2010.07.022>
- Usman M., & Hammar, N., (2021). Dynamic relationship between technological innovations, financial development, renewable energy, and ecological footprint: fresh insights based on the STIRPAT model for Asia Pacific Economic Cooperation countries, *Environmental Science and Pollution Research*, 28, 15519–15536.
- Vivid A. K., & Deni K., (2021). Decomposition of CO<sub>2</sub> emissions in ASEAN Based on Kaya Identity, *Indonesian Journal of Energy*, 4 (2), 101 – 114
- Wei L., Shu Z., & Hongzhi Z., (2017). Analysis on Influence Factors of CO<sub>2</sub> Emission in Hebei, 2017 International Conference on Advanced Environmental Engineering (ICAEE2017) IOP Publishing IOP Conf. Series: Earth and Environmental Science, 111 (2018) 012025 doi:10.1088/1755-1315/111/1/012025
- WRI, (2018). Emissions intensity in Navigating the numbers, Greenhouse gas data and international climate policy Part-1, Chapter 5. World Resources Institute
- Wu Y., Shen L., Zhang Y., Shuai C., Yan H., Lou Y., & Gui Y., (2019). A New Panel for Analyzing the Impact Factors on Carbon Emission: A Regional Perspective in China, *Ecological Indicators*, 97, 260–268. doi:10.1016/j.ecolind.2018.10.006
- Xilong C., Meijiao Z., & Longxi L., (2015). Analysis of Carbon Dioxide Emissions of Buildings in Different Regions of China Based on STIRPAT Model, 9th International Symposium on Heating, Ventilation and Air Conditioning (ISHVAC) and the 3<sup>rd</sup> International Conference on Building Energy and Environment (COBEE), *Science Direct*, Procedia Engineering 2015, 121, 645 – 652, doi: 10.1016/j.proeng.2015.08.1057
- Xiong C., Chen S., & Xu L., (2020). Driving Factors Analysis of Agricultural Carbon Emissions Based on Extended STIRPAT Model of Jiangsu Province, China, *Growth Change*, 51 (3), 1401–1416. doi:10.1111/grow.12384
- Xiongfeng P., Kamal U., Bowei A., Xianyou P., & Umme S., (2019). Influential factors of carbon emissions intensity in OECD countries: Evidence from symbolic regression, *Journal of Cleaner Production*, 220, 1194-1201, ISSN 0959-6526. <https://doi.org/10.1016/j.jclepro.2019.02.195>.

- Yang B., Usman M., & Jahanger A., (2021). Do industrialization, economic growth, and globalization processes influence the ecological footprint and healthcare expenditure? Fresh insights based on STIRPAT model for countries with the highest healthcare expenditures, *Sustainable Production and Consumption*, 28, 893–910.
- York R., Rosa, E.A., & Dietz, T., (2003) STIRPAT, IPAT and ImPACT: Analytic Tools for Unpacking the Driving Forces of Environmental impacts, *Ecological Economics*, 46, 351-365
- Zhao H., Hu J., Hao F., & Zhang H. (2022). Determinants of Carbon Dioxide Emissions and Their Peaking Prospect: Evidence from China, *Frontiers in Environmental Science*, 10, 10:913835. doi: 10.3389/fenvs.2022.913835
- Ziroat M., & Raufhon S., (2022). Renewable energy and CO2-Emissions intensity in the top carbon intense countries, *Renewable Energy*, 192, 507-512, ISSN 0960-1481, <https://doi.org/10.1016/j.renene.2022.04.137>.