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# **Interplay of Macroeconomics and CO<sub>2</sub> Emissions Dynamics: Evidence from Top CO<sub>2</sub> Emitting Economies**

**Jaganathan Maniselvam <sup>a</sup>, Kalidoss Radhakrishnan <sup>a</sup>,  
Swadesh Prakash <sup>a\*</sup> and Palsam Karthik Kumar Goud <sup>a</sup>**

<sup>a</sup> ICAR, Central Institute of Fisheries Education, Mumbai, India.

## **Authors' contributions**

*This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.*

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## **ABSTRACT**

Understanding the dynamic connection between macroeconomic factors and CO<sub>2</sub> emissions is vital for developing sustainable and environmentally conscious economic systems. Utilizing a 30-year dataset from the World Bank, focusing on the top 10 CO<sub>2</sub>-emitting nations, the study employs the Vector Error Correction Model (VECM) to capture both long-term and short-term causal relationships. Descriptive statistics showcase per capita CO<sub>2</sub> emissions averaging 8.77 metric tons with notable variability. Key economic indicators, including forest area, foreign direct investment, trade, and GDP, exhibit dynamic trends. Renewable energy consumption averages 15.02%, while energy use per capita stands at 3579.16 kg of oil equivalent. Agricultural land constitutes 32.48%, and the estimated rural population percentage is approximately 33.94%. The VAR model with nine equations is thoroughly evaluated using criteria like BIC (125.280) and HQIC (122.177), signifying

\*Corresponding author: E-mail: [swadeshprakash@cife.edu.in](mailto:swadeshprakash@cife.edu.in);

model fitting. Coefficients in the model highlight the impact of lagged values on the dependent variable, such as the statistically significant lagged CO<sub>2</sub> emissions variable at lag 1. The Impulse Response Function (IRF) illustrates dynamic responses to variable shocks. Forecast Error Variance Decomposition (FEVD) emphasizes the heavy reliance on past values for short-term CO<sub>2</sub> forecasts, with external factors gaining significance over longer horizons. This comprehensive approach enhances the understanding of variable contributions to forecast uncertainty, emphasizing the importance of integrating economic development with environmental stewardship.

**Keywords:** CO<sub>2</sub> emissions; climate change; economic growth; VECM.

## 1. INTRODUCTION

Climate change is a significant issue of our time and is increasingly alarming on a global scale. Data provided by the International Energy Agency reveals a concerning trend, carbon emissions worldwide have increased by 40% since the early 1970s (IEA, 2013). From the 21st century until 2019, there has been a consistent upward trajectory in global Greenhouse Gas (GHG) emissions, primarily driven by the surge in emissions from China and other emerging economies. Consequently, atmospheric concentrations of greenhouse gases have significantly risen, intensifying the natural greenhouse effect and potentially threatening life on Earth. The COVID-19 pandemic led to a notable deviation from this trend, with global emissions experiencing a 3.7% decrease in 2020 compared to 2019 levels. However, this interruption to the upward trend was short-lived, as global GHG emissions resumed their ascent shortly after the peak of the pandemic. By 2022, emissions had rebounded to a level of 53.8 Gt CO<sub>2</sub>eq, surpassing 2019 levels by 2.3% and 2021 levels by 1.4%. Among the various contributors to this complex phenomenon, carbon dioxide (CO<sub>2</sub>) emissions stand out as a primary concern due to their significant impact on the Earth's climate system (Ala et al., 2011). Understanding the factors driving CO<sub>2</sub> emissions is crucial for designing effective policies aimed at mitigating climate change while sustaining economic growth.

Despite extensive research on the drivers of CO<sub>2</sub> emissions (Cole and Elliott, 2003; Dinda, 2004; Grossman and Krueger, 1995; Halkos & Paizanos, 2015; Shafik and Bandyopadhyay, 1992; Stern, 2004), the dynamic nexus between macroeconomic factors and carbon output remains a complex and understudied area. Existing literature offers conflicting insights, with some studies (Ang, 2007; Cole and Neumayer, 2004; Halicioglu, 2009) highlighting a positive correlation between economic growth and CO<sub>2</sub>

emissions, while others (Jackson, 2009; Peters and Hertwich, 2008) suggest the potential for decoupling economic development from environmental degradation. The key findings from recent studies highlight the intricate relationship between renewable energy, CO<sub>2</sub> emissions, and economic growth in Southeast Asia. Wahyudi et al., 2024 examined Indonesia's renewable energy and CO<sub>2</sub> emissions from 1990 to 2021 using a Vector Error Correction Model (VECM), revealing that GDP per unit of energy use significantly drives economic growth in both the short and long term. Similarly, Premashtira et al., 2024 explored the relationships among renewable energy consumption, CO<sub>2</sub> emissions, and economic growth in Thailand (1995–2022), employing VECM methods. Their findings revealed a positive long-term impact of renewable energy consumption and CO<sub>2</sub> emissions on economic growth, with renewable energy demonstrating a bidirectional causal relationship with economic growth over time.

Against this backdrop, the primary objective of this study is to assess how different macroeconomic factors such as climate change, economic growth, energy consumption, agriculture, and rural development affect CO<sub>2</sub> emissions in top CO<sub>2</sub>-emitting nations. This study investigates the impact of macroeconomic factors on CO<sub>2</sub> emissions, focusing on the top 10 CO<sub>2</sub> emitting countries namely, China, United States, India, Russia, Japan, Korea, Iran, Indonesia, Germany, and Canada. The selection of these countries is based on their substantial contribution to global emissions and their pivotal role in shaping international climate policies. By examining the relationship between macroeconomic indicators and CO<sub>2</sub> emissions over time, this study aims to provide valuable insights into the drivers of carbon emissions and their implications for sustainable development.

Furthermore, our study carries various implications that extend to the understanding of

carbon emissions sensitivity, actions, and guidelines applicable to the general public, producers, policymakers, and government officials. As far as we know, this is the first study to assess the influence of macroeconomic factors on CO<sub>2</sub> emissions specifically in the top 10 CO<sub>2</sub> emitting nations. To accurately portray the factors influencing CO<sub>2</sub> emissions, we consider a range of indicators as proxies and analyze the top 10 CO<sub>2</sub> emitting nations globally. Methodologically, we utilize the vector error correction model (VECM) to capture both long-term and short-term causal relationships between dependent and independent variables, as well as the directional association between them. Finally, we offer insightful recommendations to enhance environmental sustainability in the studied regions based on the findings of our research. Based on empirical findings, the study offers evidence-based policy recommendations to policymakers, stakeholders, and international organizations for enhancing climate resilience and fostering low-carbon transitions in high-emission economies.

## 2. MATERIALS AND METHODS

The data for this study were gathered from the World Bank, encompassing 30-year period (1991- 2020), and focused on the top 10 CO<sub>2</sub>-emitting countries (China, United States, India, Russia, Japan, South Korea, Iran, Indonesia, Germany, and Canada). The main intuition behind this study is to explore the role of climate change, economic growth, use of energy, agriculture, and rural development in the top CO<sub>2</sub> emissions countries. The study considers CO<sub>2</sub> emissions as the dependent variable. The independent variables include the population growth rate and forest area ratio, which serve as proxies for climate change. Economic growth is represented by foreign direct investment, trade percentage rate, and gross domestic product. Energy-related factors are captured through energy use and renewable energy consumption. Agricultural land ratio and rural population rate are included as proxies for agriculture and rural development.

We examine the relationship between explanatory variables and the dependent variable using VAR-type models, specifically Vector Error Correction Model (VECM). This analysis allows us to explore both short-run and long-run relationships.

### 2.1 Vector Error Correction Model (VECM)

VECM is a powerful tool for examining Granger causality in the context of time series data, allowing researchers to understand the dynamic relationships between variables over time. In the VECM framework, the Granger causality test is applied to assess the causal relationship between variables. Granger causality essentially examines whether past values of one variable provide information about the future values of another variable. In the context of VECM and Granger causality testing, the procedure involves estimating the VECM and then assessing the significance of lagged values in predicting future values of the variables. The Granger causality test is typically conducted by comparing the restricted and unrestricted models. If the addition of lagged values significantly improves the model, it implies Granger causality.

### 2.2 Generalized Method of Moments (GMM)

After identifying the alignment of explanatory variables with carbon dioxide emissions in both the long and short run, we employ the GMM statistical approach to investigate the overall significant connection between independent variables and the dependent variable. GMM is a semiparametric model designed to address sources of heteroskedasticity in the data (Le et al., 2016). It contributes to testing the robustness of our Vector Error Correction Model (VECM) based Impulse Response Function (IRF) results. The GMM model is essentially an OLS linear regression model, and its equation is specified as follows:

$$\frac{1}{n} \sum_{i=1}^n x_i \hat{\mu}_i = \frac{1}{n} \sum_{i=1}^n x_i (y_i - x_i \hat{\beta}) = 0$$

Here,  $x_i$  indicates the vector of  $p$  covariates,  $\mu_i$  is the exogenous error term,  $\beta_0$  is the true value of  $p$  in the unknown parameters  $\beta$  and  $n$  is time series indices. In case of panel data, the moment condition  $E[(x_i, \theta_0)] = 0$  translates to  $E[x_i \mu_i] = E[x_i(y_i - x_i \beta)] = 0$ .

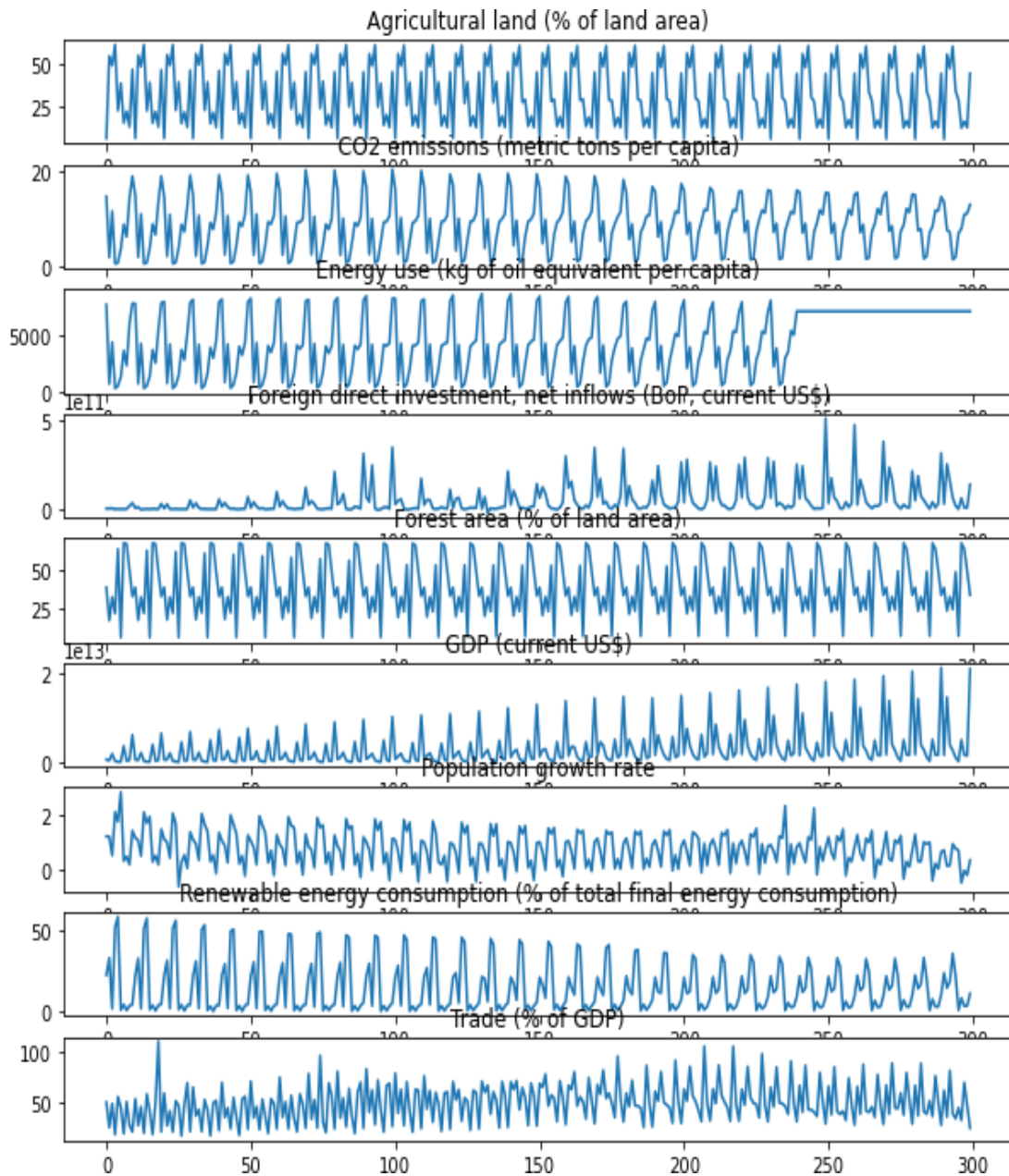
## 3. RESULTS AND DISCUSSION

### 3.1 Descriptive Statistics

The per capita CO<sub>2</sub> emissions stand at approximately 8.77 metric tons, displaying a

notable range from 0.68 to 20.47 metric tons. The population growth rate hovers around 0.76%, with relatively low variability between -0.62% and 2.8%. Key averages include 39.32% for forest area (% of land area), \$51.46 billion for foreign direct investment, 48.78% for trade (% of GDP), and \$3.12 trillion for GDP (current US\$). Renewable energy consumption averages at 15.02%, ranging moderately from 0.44% to 58.44% of total final energy consumption. Energy

use per capita averages at 3579.16 kg of oil equivalent, with moderate variability between 316.56 and 8455.55 kg. Agricultural land constitutes an average of 32.48%, displaying moderate variability from 6.37% to 61.07%. The estimated average total rural population percentage is approximately 33.94%, with a moderate spread from 8.22% to 74.22%. Trendlines for each variable are presented in Fig. 1.



**Fig. 1. Graphical plots of studied variables for the top CO<sub>2</sub> emitting countries**



### 3.2 VAR Model

The examination comprises a VAR model consisting of 9 equations. The BIC (Bayesian Information Criterion) is 125.280, utilized for model selection, with lower values indicating superior fitting models. Similarly, the HQIC (Hannan-Quinn Information Criterion) stands at 122.177, serving as an additional criterion for

model selection. The Log-likelihood is -21068.8, which measures how effectively the model elucidates the observed data. The AIC (Akaike Information Criterion) is 120.10, offering another criterion for model selection, where lower values suggest improved models. Additionally, the FPE (Final Prediction Error) is 1.483, assessing the predictive performance of the model.

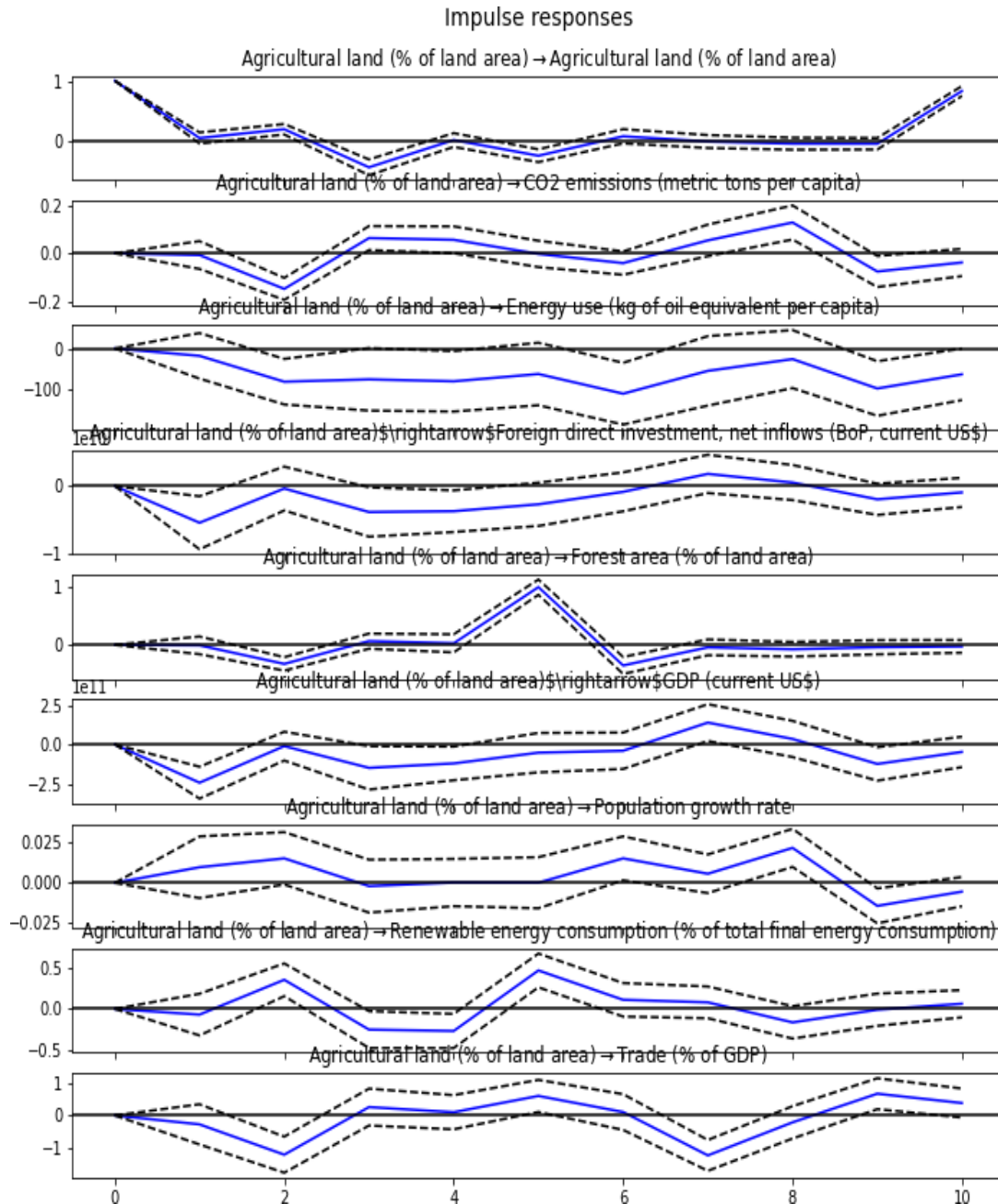
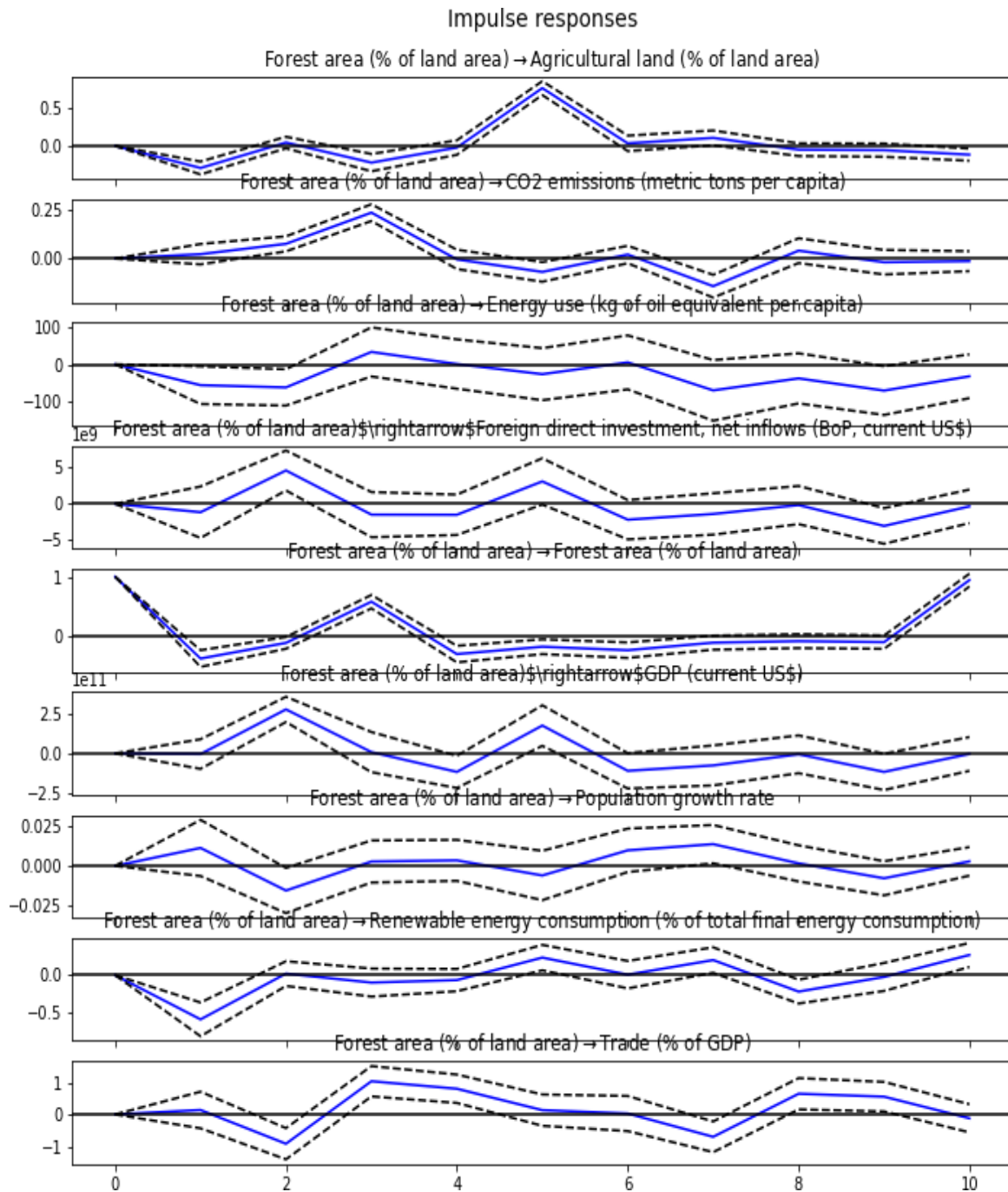


Fig. 2. Impulse response to Cholesky one standard deviation of agricultural land

The coefficients indicate the impact of lagged values of variables on the current value of the dependent variable. Standard errors provide a measure of the precision of the estimate coefficients. The coefficient for the lagged CO<sub>2</sub> emissions variable at lag 1 is -0.228. With a standard error of 0.082, this yields a t-stat of -2.781. The associated p-value for this

coefficient is 0.005 (less than 0.05), indicating the statistical significance of the lagged CO<sub>2</sub> emissions variable in forecasting current CO<sub>2</sub> emissions. The model incorporates lagged values up to lag 5 for each variable, denoted by terms such as "L1" for lag 1, "L2" for lag 2, and so forth (Hansen 1982, IPCC 2007).



**Fig. 3. Impulse response to Cholesky one standard deviation of forest land**

### 3.3 Impulse Response Function (IRF)

The Impulse Response Function (IRF) in this study has been derived using the Generalized Method of Moments (GMM), which ensures robust and efficient estimation of dynamic relationships among variables. This approach allows for the analysis of how a shock to one variable propagates through the system over time, providing valuable insights into the interactions between key factors under investigation. The Impulse Response Function

(IRF) helps to comprehend the dynamic response of variables in the system to a shock or innovation in one of the variables. The Cholesky one standard deviation novelties impulse response functions (IRFs) adjusted by Agricultural land (% land area), forest area (% land area), energy use (kg of oil equivalent per capita) and GDP (current US\$) against all other remaining variables (Figs. 2 to 5). The IRF is suitable for being able to elucidate the sign of the association and how long these upshots necessitate to take place.

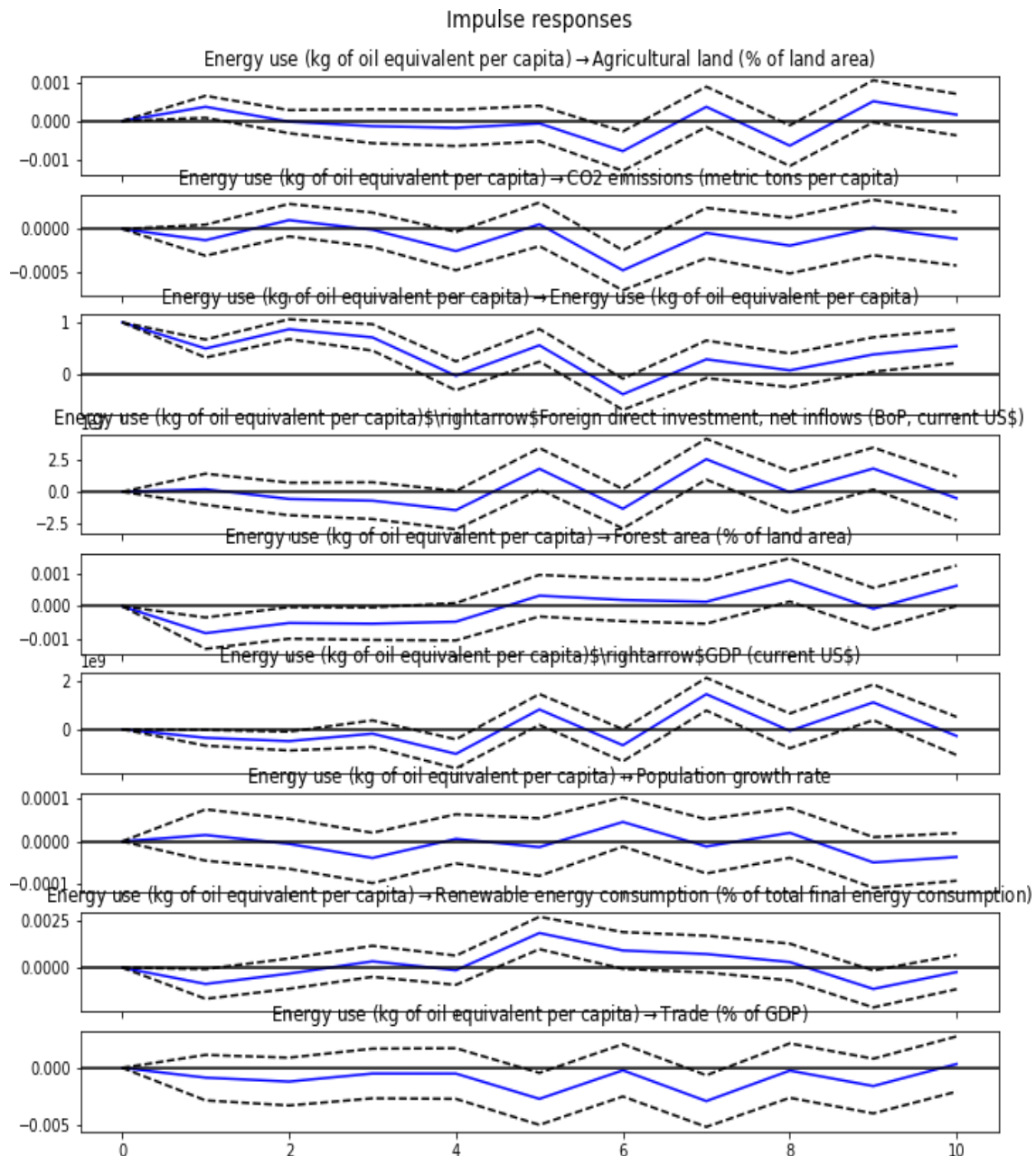


Fig. 4. Impulse response to Cholesky one standard deviation of energy use



### 3.4 Forecast Error Variance Decomposition (FEVD)

In Time Horizon 0, CO<sub>2</sub> emissions are predominantly influenced by their historical values (92.41%), indicating a strong reliance on past data for short-term forecasting. Other variables, such as agricultural land, energy use, foreign direct investment, forest area, GDP, population growth rate, renewable energy consumption, and trade, contribute negligibly. Similarly, at Time Horizon 1, CO<sub>2</sub> emissions heavily rely on their past values (84.66%), with minor contributions from agricultural land, forest area, GDP, and trade. Energy use and foreign direct investment also contribute, albeit less than CO<sub>2</sub> emissions. In Time Horizons 3 and 4, as the forecasting period extends, dependence on CO<sub>2</sub> emissions past values diminishes. Agricultural

land, energy use, forest area, GDP, population growth rate, renewable energy consumption, and trade become more significant contributors to forecast error variance. Although foreign direct investment continues to contribute, its impact decreases over time. Overall, the decomposition illustrates that while CO<sub>2</sub> emissions' own past values are crucial for short-term forecasts, the influence of external factors increases over longer horizons. Variables like GDP, renewable energy consumption, and trade exhibit notable contributions to explaining the forecast error variance of CO<sub>2</sub> emissions. This information is valuable for understanding how different variables contribute to the uncertainty in forecasting CO<sub>2</sub> emissions at various points in the future. Table 3. demonstrates Forecast Error Variance Decomposition for the studied indicators under different time horizons.

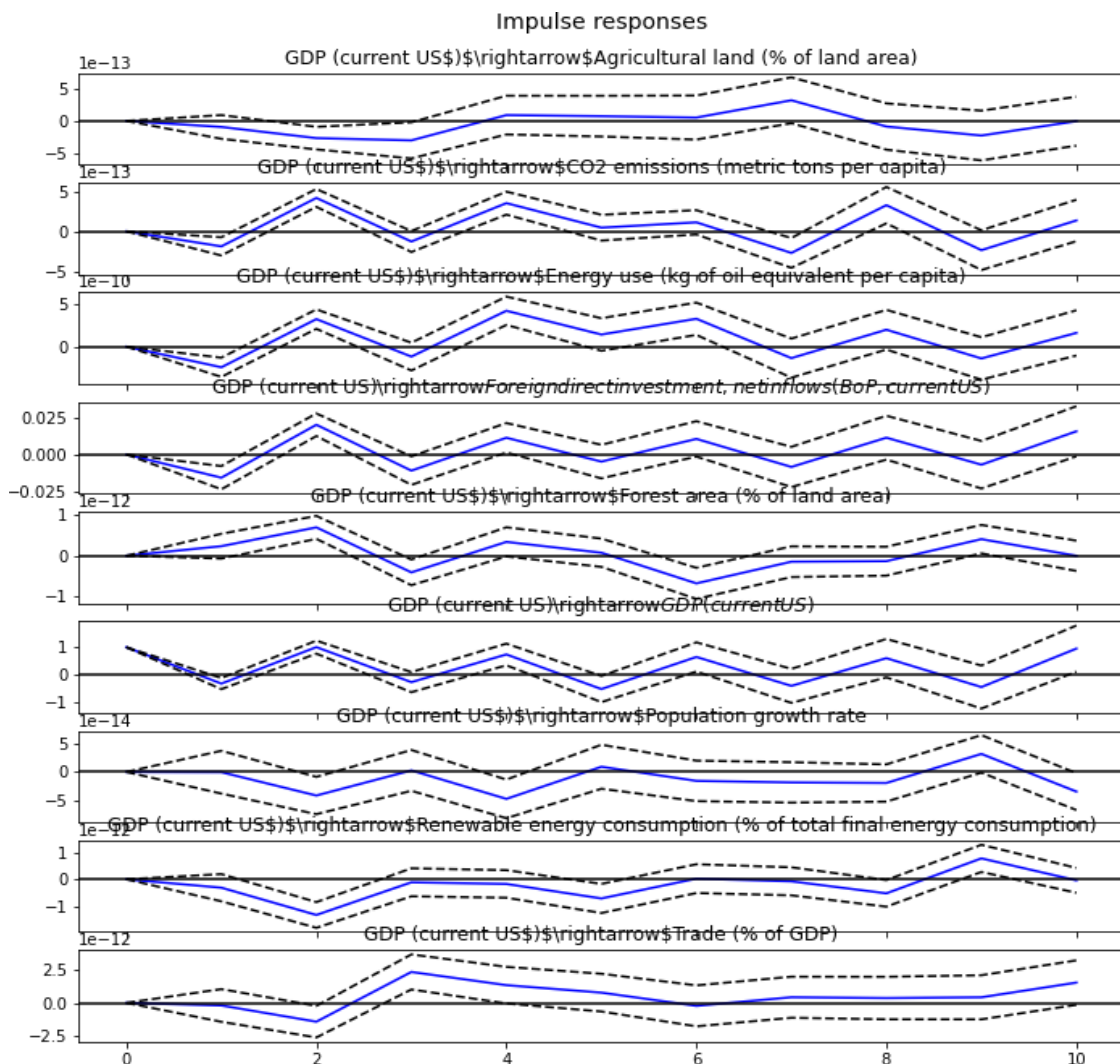


Fig. 5. Impulse response to Cholesky one standard deviation of GDP (current)

**Table 1. Descriptive statistics of the variables of top 10 CO<sub>2</sub> emitting countries**

	<b>CO<sub>2</sub> emissions</b>	<b>PGR</b>	<b>FA (% of)</b>	<b>FDI(US\$)</b>	<b>Trade (%GDP)</b>	<b>GDP (current US\$)</b>	<b>REC (%)</b>	<b>EU (kg)</b>	<b>ALR (%)</b>	<b>RP(%)</b>
Mean	8.773	0.764	39.319	51459247019	48.781	3123860417791	15.016	3579.161	32.480	33.9363
Standard Error	0.313	0.037	1.120	4954735644	1.140	250392706982	0.898	151.108	1.060	1.09676
Median	9.250	0.805	36.298	15347499705	47.979	1420332039182	7.270	3708.705	29.038	25.632
Standard Deviation	5.429	0.633	19.393	85818538731	19.746	4336928903369	15.545	2595.363	18.367	18.99645
Skewness	-0.794	-0.565	-1.023	6.8	-0.170	4.863	-0.092	-1.026	0.129	0.897632
Range	0.197	0.122	0.018	2.5	0.477	2.269	1.048	0.437	54.704	66.004
Minimum	19.787	3.420	62.906	531842419557	94.854	21317232495769	58.000	8138.987	6.370735	8.218
Maximum	20.4698	2.8	68.49383	5.11E+11	110.5771	2.14E+13	58.44	8455.547	61.07447	74.222
Sum	2631.865	229.16	11795.77	1.54E+13	14634.45	9.37E+14	4504.94	1055853	9744.092	10180.89

**Table 2. Results for equation CO<sub>2</sub> emissions (metric tons per capita)**

	<b>Coefficient</b>	<b>std. Error</b>	<b>t-Stat</b>	<b>Prob</b>
Const	5.643	7.949	0.710	0.478
L1.Agricultural land (% of land area)	-0.007	0.029	-0.248	0.804
L1.CO <sub>2</sub> emissions (metric tons per capita)	-0.229	0.082	-2.781	0.005
L1.Energy use (kg of oil equivalent per capita)	0.000	0.000	-1.422	0.155
L1.Foreign direct investment, net inflows (BoP,current US\$)	0.000	0.000	1.103	0.270
L1.Forest area (% of land area)	0.023	0.027	0.851	0.395
L1.GDP (current US\$)	0.000	0.000	-3.240	0.001
L1.Population growth rate	-0.033	0.195	-0.167	0.867
L1.Renewable energy consumption (% of total final energy consumption)	0.009	0.021	0.401	0.688
L1.Trade (% of GDP)	-0.022	0.006	-3.725	0.000
L2.Agricultural land (% of land area)	-0.195	0.027	-7.219	0.000
L2.CO <sub>2</sub> emissions (metric tons per capita)	-0.480	0.084	-5.731	0.000
L2.Energy use (kg of oil equivalent per capita)	0.000	0.000	0.766	0.443
L2.Foreign direct investment, net inflows (BoP, current US\$)	0.000	0.000	0.885	0.376
L2.Forest area (% of land area)	0.089	0.029	3.019	0.003
L2.GDP (current US\$)	0.000	0.000	6.379	0.000

	<b>Coefficient</b>	<b>std. Error</b>	<b>t-Stat</b>	<b>Prob</b>
L2.Population growth rate	-0.515	0.193	-2.666	0.008
L2.Renewable energy consumption (% of total final energy consumption)	-0.153	0.021	-7.430	0.000
L2.Trade (% of GDP)	0.012	0.006	2.029	0.042
L3.Agricultural land (% of land area)	0.083	0.030	2.760	0.006
L3.CO <sub>2</sub> emissions (metric tons per capita)	-0.054	0.099	-0.547	0.584
L3.Energy use (kg of oil equivalent per capita)	0.000	0.000	0.572	0.567
L3.Foreign direct investment, net inflows (BoP, current US\$)	0.000	0.000	0.152	0.880
L3.Forest area (% of land area)	0.179	0.022	7.974	0.000
L3.GDP (current US\$)	0.000	0.000	1.172	0.241
L3.Population growth rate	0.291	0.190	1.528	0.127
L3.Renewable energy consumption (% of total final energy consumption)	-0.085	0.021	-4.026	0.000
L3.Trade (% of GDP)	0.013	0.006	2.110	0.035
L4.Agricultural land (% of land area)	0.139	0.035	3.950	0.000
L4.CO <sub>2</sub> emissions (metric tons per capita)	0.011	0.092	0.116	0.908
L4.Energy use (kg of oil equivalent per capita)	0.000	0.000	-0.199	0.842
L4.Foreign direct investment, net inflows (BoP, current US\$)	0.000	0.000	-0.110	0.912
L4.Forest area (% of land area)	0.081	0.019	4.174	0.000
L4.GDP (current US\$)	0.000	0.000	-2.614	0.009
L4.Population growth rate	0.137	0.197	0.698	0.485
L4.Renewable energy consumption (% of total final energy consumption)	-0.076	0.018	-4.260	0.000
L4.Trade (% of GDP)	0.001	0.006	0.219	0.827
L5.Agricultural land (% of land area)	-0.031	0.038	-0.817	0.414
L5.CO <sub>2</sub> emissions (metric tons per capita)	0.072	0.084	0.852	0.394
L5.Energy use (kg of oil equivalent per capita)	0.000	0.000	-1.669	0.095
L5.Foreign direct investment, net inflows (BoP, current US\$)	0.000	0.000	-0.423	0.672
L5.Forest area (% of land area)	-0.041	0.029	-1.421	0.155
L5.GDP (current US\$)	0.000	0.000	-0.924	0.356
L5.Population growth rate	-0.012	0.201	-0.059	0.953
L5.Renewable energy consumption (% of total final energy consumption)	0.019	0.023	0.832	0.405
L5.Trade (% of GDP)	0.026	0.006	4.220	0.000
L5.Population growth rate	-0.012	0.201	-0.059	0.953
L5.Renewable energy consumption (% of total final energy consumption)	0.019	0.023	0.832	0.405
L5.Trade (% of GDP)	0.026	0.006	4.220	0.000

**Table 3. Forecast Error Variance Decomposition (FEVD)**

<b>Time Horizon</b>	<b>Agricultural land (%)</b>	<b>CO<sub>2</sub> Emissions</b>	<b>Energy Use (kg/ equ/ c)</b>	<b>FDI net Inflows (US\$)</b>	<b>Forest Area (%)</b>	<b>GDP (US\$)</b>	<b>Population Growth Rate</b>	<b>Ren.energy Cons (%)</b>	<b>Trade (% of GDP)</b>
0	0.0759	0.9241	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
1	0.0608	0.8466	0.0173	0.0003	0.0032	0.0323	0.0000	0.0002	0.0393
2	0.0514	0.6625	0.0175	0.0263	0.0041	0.0766	0.0145	0.0813	0.0659
3	0.0465	0.5613	0.0224	0.0433	0.0517	0.1063	0.0170	0.0979	0.0535
4	0.0537	0.4821	0.0192	0.0699	0.0438	0.1617	0.0175	0.0828	0.0694

#### 4. CONCLUSION AND RECOMMENDATION

This study highlights the complex interplay between macroeconomic factors and CO<sub>2</sub> emissions in the top 10 CO<sub>2</sub>-emitting nations, emphasizing both short- and long-term dynamics over a 30-year period. Using methodologies such as Vector Error Correction Models (VECM), and Impulse Response Function (IRF) which is the derivative of Generalized Method of Moments (GMM), it identifies critical drivers, including GDP, energy use, renewable energy consumption, and agricultural land. The analysis reveals that while CO<sub>2</sub> emissions are heavily influenced by their own historical values in the short term, external macroeconomic factors such as trade, foreign direct investment, and renewable energy consumption become more significant over longer horizons. Descriptive findings, such as an average per capita CO<sub>2</sub> emission of 8.77 metric tons and renewable energy consumption at just 15.02%, underscore the pressing need for sustainable energy transitions and targeted interventions to mitigate climate change.

The findings present actionable insights for policymakers aiming to achieve low-carbon economic growth. Expanding renewable energy infrastructure, implementing carbon pricing mechanisms, and promoting energy-efficient technologies are essential strategies. Fostering sustainable agricultural practices, aligning trade and foreign direct investment with environmental goals, and integrating climate resilience into development planning can significantly reduce emissions. Strengthening international cooperation through multilateral agreements and technology transfers is vital for addressing global environmental challenges. These recommendations provide a roadmap for balancing economic development with environmental stewardship in the world's highest-emitting economies, contributing to a sustainable and climate-resilient future.

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Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc.) and text-to-image generators have been used during the writing or editing of this manuscript.

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#### COMPETING INTERESTS

Authors have declared that no competing interests exist.

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