AIR QUALITY AND LAND USE UNDER ECOLOGICAL CONSTRAINT: AN ENVIRONMENTAL ASSESSMENT OF CO_2 EMISSIONS, PM2.5, AGRICULTURAL LAND USE, AND URBANIZATION IN E7 COUNTRIES

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Abstract. Environmental sustainability has emerged as a critical concern as rising emissions, land degradation, and urban expansion continue to strain ecological systems worldwide. The ecological footprint offers a holistic measure of environmental pressure by estimating the biologically productive land and water area required to support human consumption and absorb associated waste. This study examines the dynamic nexus between the ecological footprint and its key drivers—carbon dioxide (CO_2) emissions, air pollution caused by fine particulate matter with a diameter of 2.5 µm or less (PM2.5), renewable energy consumption, agricultural land use, urbanization, and green innovation— across E7 countries (China, India, Brazil, Russia, Indonesia, Mexico and Turkey) from 1990 to 2022. Utilizing the Cross-Sectionally Augmented Autoregressive Distributed Lag (CS-ARDL) model, alongside Fully Modified Ordinary Least Squares (FMOLS), Augmented Mean Group (AMG), and Dumitrescu-Hurlin panel causality tests, the analysis reveals that CO_2 emissions, PM2.5, agricultural land, and urbanization significantly intensify ecological pressure, whereas renewable energy and green innovation are effective in reducing the ecological footprint. The significant error correction term confirms long-run equilibrium, while robustness of the results across estimation methods reinforces the reliability of the findings. Causality tests further demonstrate that pollution variables and innovation exert predictive influence on the ecological footprint, underscoring their policy relevance. These insights highlight the urgent need for integrated strategies in E7 economies that curb emissions, enhance clean energy adoption, improve land management, and foster environmental innovation. By centering the ecological footprint as a multidimensional indicator of ecological stress, the study contributes meaningful evidence to guide sustainable development pathways in emerging economies.
Keywords: *CO_2 emissions, PM2.5 pollution, renewable energy, agricultural land use, green innovation, ecological footprint, CS-ARDL*

Introduction

Climate change stands as one of the most pressing global challenges, posing a substantial threat to the pursuit of sustainable development (Feng et al., 2025; Lin et al., 2025). As industries expand and technological progress accelerates, the pressure on natural ecosystems intensifies, leading to an increase in ecological footprint (EF) (Wu et al., 2024; Yasmeen et al., 2022). Without strategic intervention, future generations risk inheriting a world marked by environmental degradation and resource scarcity (Wu et al., 2025; Zhao et al., 2024). However, through sustainable pathways such as transitioning to renewable energy, improving air quality, conserving land resources, and adopting low-carbon technologies, societies can reduce environmental harm while maintaining economic growth (Pragasan and Ganesan, 2022; Rabbani et al., 2024). A balanced

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approach—where progress aligns with ecological integrity—is essential for long-term resilience. In this context, EF has emerged as a pivotal metric for assessing environmental sustainability by measuring the extent to which human demand exceeds the planet's regenerative capacity (Aslam et al., 2023; Li et al., 2023).

According to Resource Dependency Theory, economies heavily reliant on extractive activities, such as extensive agricultural land use, may experience long-term ecological degradation due to land conversion, deforestation, and soil erosion (Bekun et al., 2021; Wang et al., 2025). This issue is particularly relevant for E7 nations where food security, economic expansion, and land exploitation are deeply intertwined. Therefore, this study examines how agricultural land use contributes to environmental strain.

In contrast, renewable energy serves as a countermeasure by reducing reliance on carbon-intensive sources. As energy demand accelerates in E7 countries, clean energy adoption is expected to play a central role in reducing CO_2 emissions and PM2.5 concentrations (Qiu et al., 2023; Yang et al., 2025). Sustainable Development Theory provides a robust framework for integrating environmental protection into economic planning. Within this framework, green innovation (GI) acts as a lever to decouple economic growth from ecological harm through advancements in cleaner technologies, emissions controls, and energy efficiency (Hu et al., 2023).

PM2.5 and CO_2 emissions are included as critical stressors that directly reflect environmental degradation linked to fossil fuel combustion, industrial processes, and urban congestion. Their inclusion helps capture air quality and broader ecological health, offering a more comprehensive assessment of sustainability (Wang, 2024).

Urban Ecology Theory provides the basis for analyzing the dual role of urbanization (UB). While urban growth may increase energy consumption and environmental pressure, sustainable urban planning can offset its negative effects. Hence, understanding UB's impact on EF is essential, particularly in fast-urbanizing E7 economies.

Together, the SRU model incorporates land use (AG), pollution (PM2.5, CO_2), energy transformation (RE), technological progress (GI), and demographic shifts (UB) to analyze the structural determinants of EF. Each variable is theoretically grounded and empirically relevant to the sustainability discourse within E7 nations.

The E7 economies—Brazil, China, India, Indonesia, Mexico, Russia, and Turkey—are experiencing rapid industrialization and urban growth. These dynamics heighten emissions and strain natural resources, making the environmental actions of E7 nations crucial to global sustainability goals (Tong et al., 2020). As major contributors to global output and carbon emissions, their environmental governance and policy responses hold significant implications for ecological stability worldwide (Yang et al., 2025).

Environmental sustainability in E7 requires addressing high carbon emissions, escalating PM2.5 levels, intensive land use, and inefficient energy systems. Unchecked economic expansion has led to the overuse of land for agriculture, increased fossil fuel reliance, and poor air quality, all of which intensify EF (Kumail et al., 2020). Although some developed countries have implemented effective environmental regulations and clean energy transitions, the E7 nations still grapple with trade-offs between growth and ecological protection. Their development trajectories make them vital stakeholders in shaping both regional and global environmental futures (Dhayal et al., 2024).

Despite growing literature on sustainability, there remains a notable gap regarding how critical variables—such as renewable energy (RE), agricultural land use (AG), CO_2 emissions, PM2.5 air pollution, urbanization (UB), and green innovation (GI)—jointly influence ecological footprints in E7 countries. While several countries have launched

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green initiatives such as RE adoption and emissions trading schemes, overall environmental progress remains constrained by continued fossil fuel dependence and weak enforcement of regulations (Zhang et al., 2023). This study addresses this gap by developing an integrated empirical framework that investigates the interplay between ecological stressors and sustainability drivers in E7 economies.

Furthermore, PM2.5 and CO_2 emissions are major environmental threats in these nations, contributing to both ecological degradation and adverse public health outcomes (Aydin et al., 2019). Agricultural land expansion, often driven by economic growth, intensifies deforestation and land-use change, reducing biodiversity and increasing EF. On the other hand, renewable energy serves as a critical lever in mitigating carbon intensity and promoting low-impact development. Existing studies have largely overlooked how these key variables—especially PM2.5 and land use—contribute to environmental performance when considered jointly. By addressing this gap, the study offers a novel contribution to sustainability discourse in emerging economies.

The paper reviews the relevant literature on ecological sustainability drivers, outlines the methodology and data, presents and discusses the empirical results, and concludes with key policy implications.

Literature review

Agricultural land use and ecological footprints

Agricultural land use (AG), representing the share of land allocated for farming and livestock, is a significant determinant of ecological degradation. Expanding agricultural areas often leads to deforestation, biodiversity loss, and increased greenhouse gas emissions. Empirical evidence confirms the environmental trade-offs associated with agricultural expansion. For instance, Kurniawan and Managi (2018) emphasize that extensive land conversion, particularly in tropical regions, intensifies EF by reducing carbon sinks and increasing soil degradation. Similarly, Zambrano-Monserrate and Ormeño-Candelario (2023) found that agricultural land expansion across 24 developing nations was positively associated with rising EF, particularly when linked to monoculture and chemical-intensive practices. In South Asia, Nguyen et al. (2024) demonstrated that agricultural intensification raises short-term productivity at the expense of long-term ecological stability, while Lin and Ullah (2024) noted that cleaner agricultural practices, if supported by renewable technologies, could mitigate environmental impacts. The existing literature strongly suggests that agricultural land use, without sustainability considerations, contributes significantly to ecological deterioration. Thus, this study proposes:

H1: Increases in the share of agricultural land use are associated with significant increases in ecological footprints in E7 countries.

Renewable energy consumption and ecological footprints

The shift to renewable energy (RE) is central to global sustainability agendas. Numerous studies confirm that increasing RE consumption reduces EF by displacing fossil fuels and lowering air pollutants such as CO_2 and PM2.5 (Raza et al., 2024a, b). Sharma et al. (2021) highlight how wind and solar energy adoption improves air quality and reduces ecological stress. However, the overall impact depends on energy policy design and deployment efficiency. For example, Wang et al. (2023) found that RE alone

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cannot significantly lower EF unless accompanied by infrastructure upgrades and stable regulatory frameworks. In India, Sahoo and Sethi (2022) noted that RE policies failed to reduce GHGs due to parallel reliance on coal. Nonetheless, the consensus remains that RE is a vital strategy for mitigating EF, especially in economies like E7, where energy intensity is high. Therefore:

H2: Higher levels of renewable energy consumption are significantly associated with reductions in ecological footprints in E7 countries.

PM2.5 and ecological footprints

PM2.5, or fine particulate matter, is a direct byproduct of industrial activity, fossil fuel combustion, and unsustainable land use. Elevated PM2.5 levels pose not only health risks but also reflect broader ecological stress. According to Gupta et al. (2022), PM2.5 concentrations are strongly linked with urban sprawl and poor energy management, which increase EF. Nathaniel et al. (2021a) emphasize that E7 economies are particularly vulnerable due to weak environmental enforcement and rapid urban-industrial growth. Studies by Dhayal et al. (2023) and Sarkodie (2020) further corroborate that mitigating PM2.5 through clean energy transitions and regulatory mechanisms significantly improve sustainability metrics. Despite its exclusion in many ecological models, PM2.5 serves as a critical indicator of air quality and ecosystem degradation. Hence:

H3: Rising PM2.5 air pollution levels significantly increase ecological footprints in E7 countries.

CO_2 emissions and ecological footprints

CO_2 emissions remain the dominant contributor to global ecological degradation. Numerous studies establish a robust, positive association between CO_2 emissions and EF (Belzer et al., 2007). The combustion of fossil fuels for electricity, industry, and transport is a primary driver of CO_2 output in E7 nations. While some argue that industrial efficiency can reduce emissions over time, empirical findings (Apergis, 2016) suggest that without stringent policies, emissions will continue to expand alongside GDP. Furthermore, the pollution haven hypothesis asserts that emission-intensive industries often relocate to developing economies with lenient regulations, exacerbating their EF. Thus:

H4: CO_2 emissions exert a positive effect on ecological footprints in E7 countries.

Urbanization and ecological footprints

Urbanization (UB) has a dual impact on environmental sustainability. On one hand, it can foster resource efficiency through economies of scale; on the other, unplanned urban expansion often escalates EF by increasing energy and land demand. Danish et al. (2020) and Kazemzadeh et al. (2023a) found that UB is a major driver of EF in BRICS and MENA countries due to infrastructure development and motorization. However, Aziz et al. (2023) and Nathaniel et al. (2021a) argue that with sustainable planning, UB can reduce per capita emissions and resource use. In the E7 context, the effect of UB on EF remains context-dependent, often moderated by policy quality and investment in green infrastructure. Hence:

H5: Higher urbanization rates are associated with increased ecological footprints in E7 countries.

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Green innovation and ecological footprints

Green innovation (GI) represents a strategic response to environmental degradation by enabling low-carbon technologies, sustainable production, and energy efficiency. Dhayal et al. (2023) and Ang (2009) found that GI significantly reduces EF in both developed and emerging economies. However, the "rebound effect"—where efficiency gains reduce costs and increase consumption—poses a challenge (Ahmed et al., 2020). The net environmental benefit of GI depends on the scale of adoption and integration into national strategies. In E7, where industrial transformation is ongoing, GI has the potential to shift development onto a more sustainable path, especially when supported by institutional reforms and fiscal incentives (Shi and Yu, 2024). Thus:

H6: Increases in green innovation activity significantly reduce ecological footprints in E7 countries.

Literature gap

This study addresses critical gaps in understanding how key environmental, structural, and technological factors influence ecological footprints (EF) within the E7 economies. Unlike previous studies that focus on limited drivers or narrowly defined models, this research incorporates an integrated framework that centers on PM2.5 air pollution, CO_2 emissions, agricultural land use, renewable energy consumption, urbanization, and green innovation. These variables are not only empirically underexplored in the context of the E7 countries but are also central to the challenges these rapidly growing economies face in aligning economic development with environmental sustainability.

A major contribution of this study lies in the inclusion of PM2.5, a critical but often overlooked environmental health variable. While most prior ecological footprint studies focus on carbon emissions alone, PM2.5 provides a broader measure of air quality deterioration linked to industrialization and urban congestion. Its integration into the EF framework enables a more nuanced understanding of how environmental degradation manifests in emerging economies.

The study also advances literature by examining the role of agricultural land expansion as a structural driver of ecological strain. In E7 nations where agricultural production is closely tied to economic survival, land-use change contributes to deforestation, soil degradation, and biodiversity loss—factors that are not always captured in conventional emissions-based models.

Moreover, while the beneficial effects of renewable energy (RE) are well-documented, this study investigates its role within a broader ecological context, examining whether increased RE use can offset the environmental burdens posed by industrial activity and urban growth. The inclusion of urbanization (UB) allows us to assess how demographic shifts and infrastructure expansion affect EF across diverse development stages.

Green innovation (GI) is incorporated as a transformative mechanism capable of decoupling economic activity from ecological damage. While some literature has addressed GI in high-income contexts, its application in the E7 remains underdeveloped. This study evaluates how eco-technological advancements may mitigate EF when supported by policy and institutional frameworks.

Methodologically, the study employs the Cross-Sectionally Augmented ARDL (CS-ARDL) approach to account for both short-run dynamics and long-run equilibria in the presence of cross-sectional dependence. Robustness is ensured through FMOLS and AMG estimators, addressing endogeneity and heterogeneity concerns.

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In sum, this study fills key literature gaps by introducing a more comprehensive set of environmental indicators into the EF analysis, providing E7-specific insights that are both academically novel and policy-relevant. It also aligns with SDGs 11 (sustainable cities), 12 (responsible consumption), and 13 (climate action), offering a foundation for data-driven environmental planning and sustainable development.

Thus, this paper aims to explore the following key research questions:

1. How do CO_2 emissions and PM2.5 pollution influence ecological footprints in E7 economies?
2. What is the role of agricultural land expansion in shaping environmental degradation?
3. To what extent does renewable energy mitigate ecological pressure in E7 nations?
4. How does urbanization affect ecological sustainability in the E7 context?
5. What impact does green innovation have on ecological footprints?
6. How can policymakers balance economic transformation with environmental protection in high-emission, land-intensive E7 economies?

To investigate these questions, the study utilizes annual panel data from 1990 to 2022 across the E7 nations, capturing the evolution of environmental and economic patterns during a period of industrial transition. The econometric strategy employs the Cross-Sectionally Augmented Autoregressive Distributed Lag (CS-ARDL) model, which effectively handles cross-sectional dependence and heterogeneous dynamics common to globally integrated economies. To ensure robustness, the analysis is supplemented with Fully Modified Ordinary Least Squares (FMOLS), Augmented Mean Group (AMG) estimators, and Dumitrescu-Hurlin panel causality tests.

Although this study provides a comprehensive empirical framework, it is constrained by the exclusion of certain institutional indicators due to data limitations. Future research may incorporate governance quality or regulatory stringency to enrich the analysis. Nonetheless, the findings provide vital evidence for policymakers, environmental economists, and international institutions seeking to promote sustainable development. By emphasizing the roles of PM2.5, CO_2, renewable energy, and agricultural land in shaping ecological outcomes, this study contributes actionable insights to support the design of environmentally responsive growth strategies in E7 economies.

Methodology

This study investigates the relationship between ecological footprints (EF) and key environmental and socio-economic variables including PM2.5 air pollution (PM25), CO_2 emissions (CO2), agricultural land use (AG), renewable energy consumption (RE), urbanization (UB), and green innovation (GI) within the E7 economies. The conceptual framework draws upon three complementary theories—Resource Dependency Theory (RD), Sustainable Development Theory (SD), and Urban Ecology Theory (UE)—combined into the SRU Model. This integrated model provides a comprehensive lens to understand how energy transitions, pollution levels, land use, and technological and urban developments influence environmental sustainability in emerging markets (Ramadan and Hassan, 2022).

To empirically validate this framework, the study utilizes a Cross-Sectionally Augmented Autoregressive Distributed Lag (CS-ARDL) model. This method effectively

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handles cross-sectional dependence and heterogeneous dynamics across countries, making it suitable for the E7 context. Robustness is ensured through Fully Modified Ordinary Least Squares (FMOLS) and Augmented Mean Group (AMG) estimators, while the Dumitrescu-Hurlin panel causality test is employed to assess the directional relationships.

Based on this conceptual foundation, the functional form of the model is:

$$EF = f(PM2.5, CO_2, AG, RE, UB, GI) \quad \text{(Eq.1)}$$

This equation denotes that the ecological footprint (EF) is functionally dependent on the following factors:

- PM2.5: Concentration of fine particulate matter (air pollution)
- CO_2: Carbon dioxide emissions
- AG: Agricultural land use (% of total land)
- RE: Renewable energy consumption (% of total final energy use)
- UB: Urbanization (% of total population living in urban areas)
- GI: Green innovation (e.g., environmental technology patent applications)

Equation 1 can be represented in logarithmic form as given in *Equation 2*.

$$lEF_{i,t} = \alpha + \beta_1 lPM_{i,t} + \beta_2 lCO2_{i,t} + \beta_3 lAG_{i,t} + \beta_4 lUB_{i,t} + \beta_5 lRE_{i,t} + \beta_6 lGI_{i,t} + \varepsilon_{i,t} \quad \text{(Eq.2)}$$

This log-linear form estimates the elasticity of ecological footprint with respect to each explanatory variable.

- α: Intercept term
- β1 to β6: Elasticity coefficients
- $\varepsilon_{i,t}$: Error term

Furthermore, *Equation 3* is used to test for CSD in a panel data model, following the approach introduced by Bersvendsen and Ditzen (2020). The equation is designed to assess the presence of interdependence among different cross-sections in the dataset.

$$CSD = \sqrt{\frac{2T}{N(N-1)}\left(\sum_{i=1}^{n-1}\sum_{j=i+1}^{n}\partial_{ij}^{t}\right)} \quad \text{(Eq.3)}$$

This test checks for cross-sectional dependence (CSD) in the residuals.

- T: Number of time periods
- N: Number of cross-sectional units (countries)
- ∂_{ij}^{t}: Correlation between residuals of country i and j at time t

The CSD test determines whether cross-sectional units are interdependent or not. If the test result is significant, it suggests that shocks or disturbances in one country may influence others, meaning that cross-sectional dependence exists. Moreover, after testing CSD, the study examines slope homogeneity, which determines whether the relationships between independent and dependent variables remain consistent across all cross-sectional units or vary among them. This is important because if the slopes are heterogeneous, applying panel estimation techniques that assume homogeneity may lead to biased results.

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For this purpose, the slope homogeneity test of Hashem Pesaran and Yamagata (2008) is used for this purpose, represented by the following two equations:

$$\widetilde{\Delta} = \sqrt{N}\left(\frac{N^{-1}\tilde{S}-K}{\sqrt{2K}}\right) \quad \text{(Eq.4)}$$

This test statistic examines whether slope coefficients are the same across all units.

- $\tilde{S}$: Sum of squared slope deviations
- K: Number of explanatory variables
- N: Number of cross-sectional units

$$\widetilde{\Delta}_{\text{adj}} = \sqrt{N}\left(\frac{N^{-1}\tilde{S}-E(\tilde{Z}_{iT})}{\sqrt{\text{var}\,(\tilde{Z}_{iT})}}\right) \quad \text{(Eq.5)}$$

This adjusted statistic improves accuracy by using expectations and variance of the standardized slope deviations.

- $E\left(\tilde{Z}_{iT}\right)$: Expected value of standardized slope
- var $\left(\tilde{Z}_{iT}\right)$: Variance of standardized slope

Once the slope homogeneity is checked, the next step is to check the stationarity properties of variables. According to the literature, if CSD is present, first-generation unit root tests are unsuitable. Instead, second-generation tests, such as CIPS and CADF, are preferred. In this study, we applied the CIPS unit root test to assess whether the variables are stationary or not. The test statistics for CIPS are calculated using the following equation:

$$CIPS = \frac{\hat{\delta}}{\text{se}\,(\hat{\delta})} \quad \text{(Eq.6)}$$

This second-generation unit root test accounts for CSD in testing for stationarity.

- $\hat{\delta}$: Estimated coefficient from individual CADF regressions
- se ($\hat{\delta}$): Standard error of the estimate

The CIPS test is one of the most crucial methods for assessing stationarity. Its significance lies in its ability to account for CSD for panel datasets. Furthermore, it improves inference accuracy by reflecting the cross-sectional structure in panel data. This arrangement makes it a valuable tool for scholars targeting to achieve robust and reliable findings under analysis. Once the unit root of variables is verified, the next step involves performing a co-integration test to examine the long-term relationships among variables. If the CSD test indicates significant CSD, the Kao co-integration test is not suitable. Instead, this study employs the co-integration Westerlund co-integration approach of Westerlund (2007) which effectively addresses CSD, confirming more precise and reliable inference in panel data models. Westerlund's approach is particularly advantageous in co-integration analysis, as it enhances the validity of findings by incorporating CSD into the estimation process.

$$G_t = \frac{1}{N}\sum_{i=1}^{N} \frac{\partial_i^{!}}{SE\,\partial_i^{!}} \quad \text{(Eq.7)}$$

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$$G_a = \frac{1}{N}\sum_{i=1}^{N} \frac{T\,\partial_i^!}{\partial_i^!(1)} \quad \text{(Eq.7.1)}$$

$$P_t = \frac{\partial^!}{SE(\partial^!)} \quad \text{(Eq.7.2)}$$

$$\partial^! = \frac{P_a}{T} \quad \text{(Eq.7.3)}$$

These statistics test for group-wise co-integration across countries.

- $\partial_i^!$: Error correction term for country i
- $SE(\partial^!)$: Standard error of the error correction term
- $\partial^!$: Pooled error correction term
- P_a: Adjusted panel statistic
- T: Time dimension

After checking co-integration, the next step is to estimate the long-run and short-run relationships between variables using CS-ARDL. This approach is particularly useful in panel data assessment as it accounts for CSD and heterogeneity across units. The CS-ARDL model is represented by the following equation:

$$y_{i,t} = \alpha_i + \sum_{l=1}^{p_y} \tau_{l,i} y_{i,t-l} + \sum_{l=0}^{p_x} \beta_{l,i} x_{i,t-l} + \sum_{l=0}^{p_\sigma} \sigma'_{i,l} \bar{z}_{i,t-l} + \varepsilon_{i,t} \quad \text{(Eq.8)}$$

- The term $y_{i,t}$ is the dependent variable for country *i* at time *t*.
- Whereas NR, RE, CF, UB, FDI, and GI are among the independent variables that make up x.
- Coefficient of the dependent variable is represented by $\emptyset$.
- The short-run coefficients are denoted by α_i, π_i, ω_i, ψ_i, Ω_i, and $¥_i$, while the long-run coefficients are represented by β1 to β6.

Furthermore, the econometric process employed has been shown in *Figure 1*.

The study employs annual panel data for the E7 economies from 1990 to 2022, sourced from reputable and globally recognized databases. Specifically, ecological footprint (EF) data is obtained from the Global Footprint Network (GFN), while CO_2 emissions (CO2), PM2.5 air pollution, renewable energy consumption (RE), agricultural land use (AG), and urbanization (UB) are sourced from the World Development Indicators (WDI). The green innovation (GI) indicator is extracted from the OECD database.

The variables units and sources are mentioned in *Table 1*.

Table 1. *Variable description and data sources*

Variable	Short form	Unit	Data source	URL
Ecological footprint	EF	Global hectares per capita	GFN	https://data.footprintnetwork.org
CO_2 emissions	CO2	Metric tons per capita	WDI	https://databank.worldbank.org/source/world-development-indicators
PM2.5 air pollution	PM25	μg/m³	WDI	https://databank.worldbank.org/source/world-development-indicators
Renewable energy	RE	% of total energy use	WDI	https://databank.worldbank.org/source/world-development-indicators
Agricultural land	AG	% of land area	WDI	https://databank.worldbank.org/source/world-development-indicators
Urbanization	UB	% of total population	WDI	https://databank.worldbank.org/source/world-development-indicators
Green innovation	GI	Epsilon-based index	OECD	https://stats.oecd.org/Index.aspx?DataSetCode=PATS_IPC

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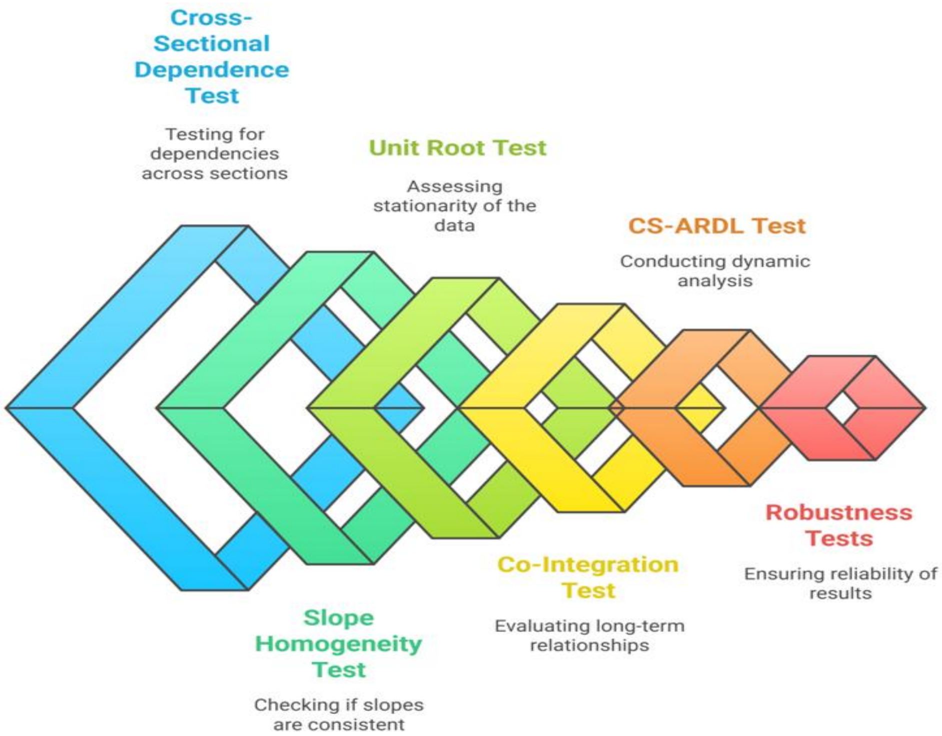

Figure 1. *Econometric analysis process*

Results

Figure 2 illustrates the trends of key variables across E7 countries from 1990 to 2022. This figure presents the temporal trends of key environmental indicators in E7 countries—China, India, Brazil, Russia, Turkey, Mexico, and Indonesia—from 2000 to 2022. The indicators include ecological footprint, CO_2 emissions, $PM_{2.5}$ air pollution, and renewable energy. Russia has consistently maintained the highest EF levels, although it saw a decline in the early 1990s followed by fluctuations. China shows a steady increase in EF, reflecting industrial expansion. Brazil, Mexico, and Turkey exhibit moderate trends with signs of recent stabilization. In contrast, India and Indonesia have maintained lower EF levels, though they show an upward trajectory over time. These differences reflect varying policy responses, stages of industrialization, and environmental awareness within E7.

Table 2 provides an overview of the descriptive statistics for the key variables used in this study. The average EF across E7 countries is 2.745 per capita, with a maximum of 6.878 observed in high-consumption economies. The mean CO2 emissions stand at 4.321 metric tons per capita, while PM2.5 pollution averages around 39.52 µg/m³, reflecting air quality concerns. Renewable energy (RE) consumption has a mean of 25.40%, indicating a moderate transition toward clean energy. Agricultural land (AG) accounts for an average of 42.81% of total land use, with variation across countries. Urbanization (UB) and green innovation (GI) show relatively high variation, suggesting different development and policy contexts within the E7. *Table 2a* gives the country specific descriptive statistics for the key variables used in this study.

As a prerequisite for CS-ARDL modeling, the study tests cross-sectional dependence (CSD) and slope homogeneity. *Table 3* confirms significant cross-sectional dependence among the E7 countries, highlighting the spillover effects of environmental practices and

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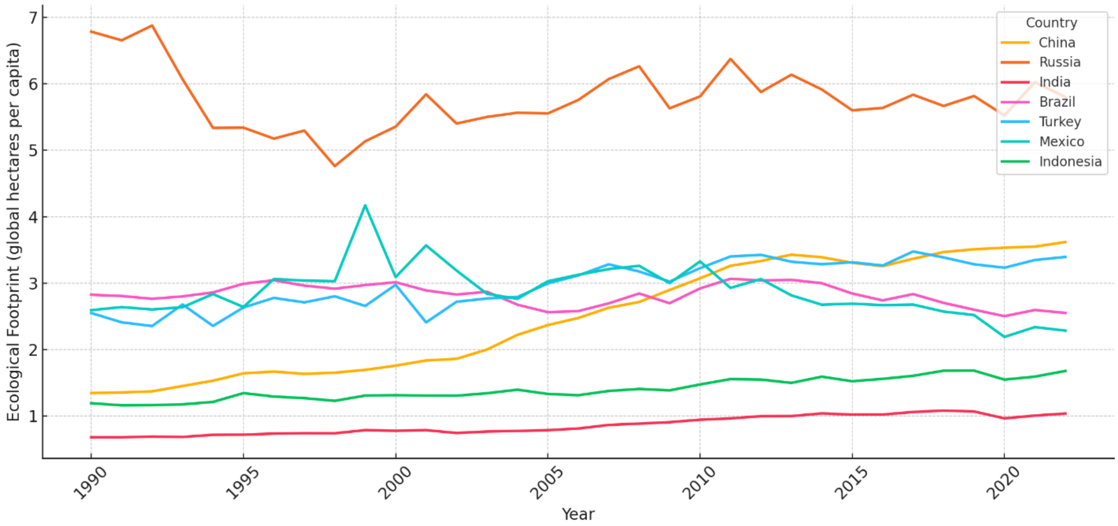
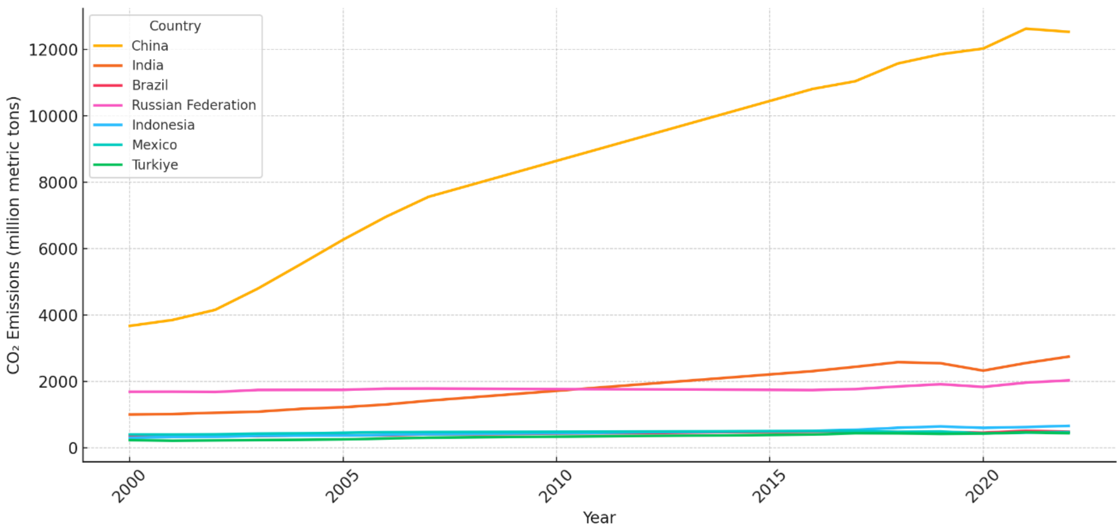
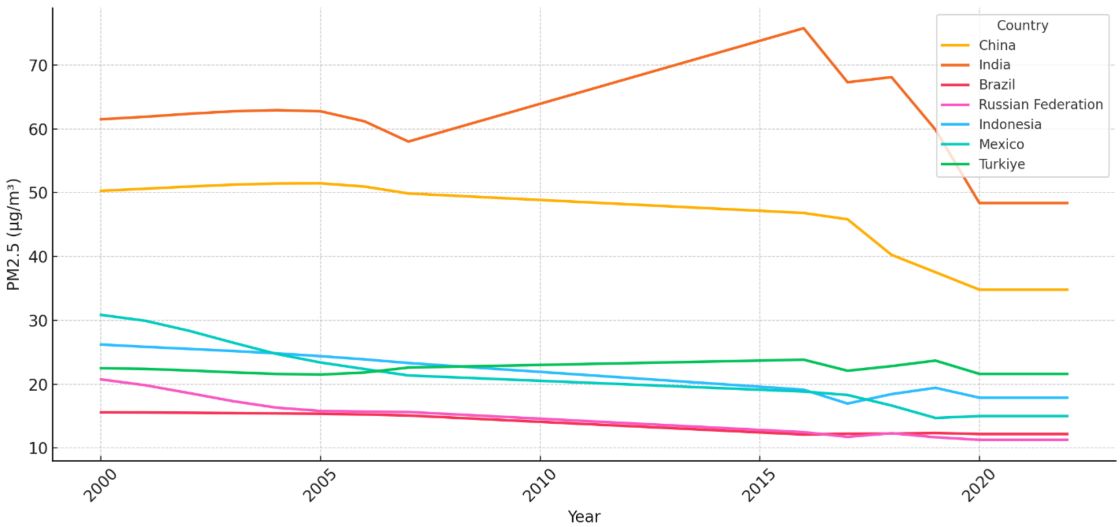
shared regional challenges. *Table 4* presents the results of the slope homogeneity test, with significant Delta and Adjusted Delta statistics, implying heterogeneous effects across countries. These findings validate the need for econometric models capable of handling both interdependencies and country-specific dynamics.







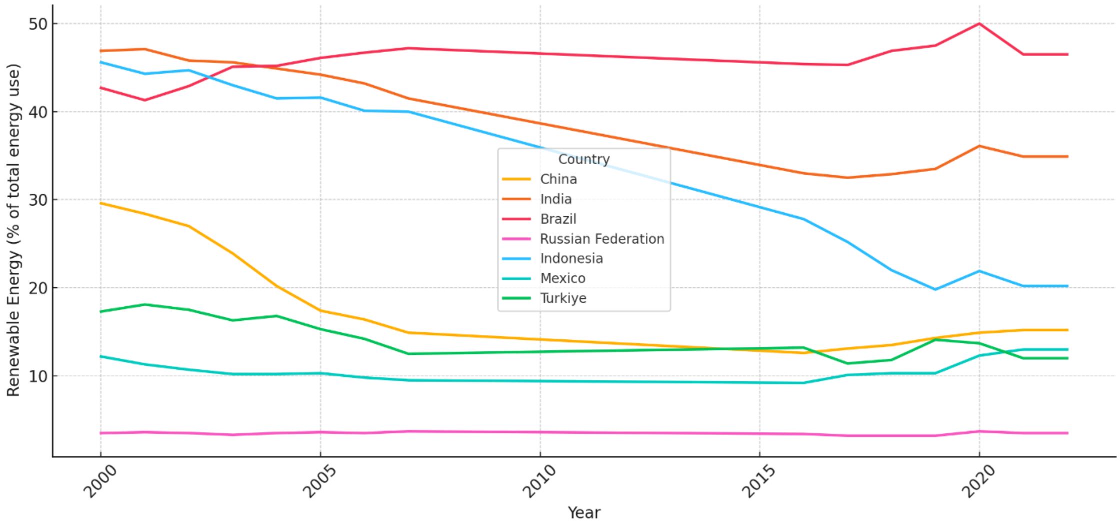


Figure 2. *Trends in ecological footprint, CO_2 emissions, PM2.5 air pollution, and renewable energy use in E7 countries (2000–2022). Data for the ecological footprint were obtained from the Global Footprint Network (https://data.footprintnetwork.org), while all other variables were sourced from the World Development Indicators (WDI), World Bank (https://databank.worldbank.org/source/world-development-indicators)*

Given the presence of CSD, the study applies the Cross-Sectionally Augmented Im-Pesaran-Shin (CIPS) unit root test, as shown in *Table 5*. The results indicate that while some variables such as GI and EF are stationary at level, most variables become stationary after first differencing. All series are integrated of order one, I(1), making them suitable for cointegration and long-run modeling.

Table 6 reports the results from the Westerlund and Edgerton (2007) co-integration test. All four test statistics (Gt, Ga, Pt, and Pa) are significant at the 1% level, confirming the presence of long-run equilibrium relationships among the variables. This result justifies the use of the CS-ARDL estimator for analyzing both long- and short-term dynamics within the E7 panel.

The diagnostic tests conducted prior to CS-ARDL application reveal several critical insights. The CSD test confirms that environmental outcomes in one E7 countries are likely influenced by developments in others, reinforcing the necessity of a cross-national approach. The heterogeneity test supports the presence of country-specific effects, indicating that one-size-fits-all policy solutions may not be effective.

Table 2. *Overall descriptive statistics*

Statistic	EF	CO_2	PM2.5	RE	AG	UB	GI
Mean	2.7454	4.3211	39.5240	25.4039	42.8050	60.1521	11.6812
Median	2.7029	4.0780	38.1000	21.2430	43.2100	68.4500	11.5000
Maximum	6.8777	10.3260	85.3000	58.6528	70.1500	87.7609	40.4000
Minimum	0.6801	0.9200	11.2000	3.1800	10.4700	25.5470	1.0300
Std. Dev.	1.5080	2.1300	14.8700	17.0928	13.4200	19.4840	5.7208
Skewness	0.8411	0.7100	0.8320	0.2957	-0.1800	-0.4676	0.2648
Kurtosis	3.1657	2.8120	3.7060	1.6688	2.7890	1.7339	1.4558

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Table 2a. *Country wise descriptive statistics*

Country	Statistic	EF	CO_2	PM2.5	RE	AG	UB	GI
Brazil	Mean	0.0954	2.5576	21.8161	31.5799	38.7933	44.3844	17.2013
Brazil	Median	3.2261	3.6707	51.5454	51.7004	44.0296	50.3657	7.6783
Brazil	Maximum	2.1624	5.0157	59.5924	24.7874	16.1666	78.0003	9.8123
Brazil	Minimum	1.7246	6.3686	38.4543	52.1554	39.8564	66.5606	9.445
Brazil	Std. Dev.	3.6575	3.3137	54.3723	-19.3976	47.5853	49.8197	3.338
Brazil	Skewness	4.2865	3.9301	44.8722	39.4545	62.6038	70.1587	13.3679
Brazil	Kurtosis	4.1369	1.9967	29.9722	26.8885	35.8552	62.043	13.168
China	Mean	2.7477	5.1685	40.4114	38.2581	29.5268	69.3851	12.9765
China	Median	2.3881	8.281	75.976	38.9266	35.2116	42.2212	19.1307
China	Maximum	0.6169	4.6866	36.6731	9.8495	44.1353	90.3737	2.5173
China	Minimum	2.109	4.8609	43.9829	49.3878	36.0534	44.8766	12.7324
China	Std. Dev.	2.2259	4.1637	39.0063	1.4283	22.0211	53.8698	13.1613
China	Skewness	1.5366	0.2906	22.2236	35.4353	43.7187	76.0136	16.1364
China	Kurtosis	2.4981	4.2643	56.4338	62.8568	28.5651	36.1481	4.6294
India	Mean	0.7593	4.9355	51.1689	21.2039	53.8843	39.2676	3.0454
India	Median	3.5229	2.8199	56.6672	12.5111	42.9742	69.5582	9.1349
India	Maximum	3.1855	8.2381	27.3739	10.1893	62.2774	55.7925	16.5615
India	Minimum	3.1157	5.315	53.778	11.4496	39.2536	74.073	12.9003
India	Std. Dev.	3.2597	1.8183	45.6292	24.0816	79.2503	69.3781	4.5793
India	Skewness	1.72	5.6988	51.6865	31.2337	51.1839	58.7298	12.6671
India	Kurtosis	3.0884	2.2732	67.5925	30.1314	31.3141	43.6375	13.8763
Indonesia	Mean	1.4142	6.533	47.9692	21.3504	36.4761	64.3709	7.9078
Indonesia	Median	2.9706	1.4269	56.3264	17.1003	57.3919	61.0387	16.5389
Indonesia	Maximum	2.8273	2.3506	53.6392	26.8	43.6614	47.4438	7.1626
Indonesia	Minimum	1.0255	5.4016	49.1606	64.9807	28.3582	101.9569	11.026
Indonesia	Std. Dev.	3.2767	5.399	34.854	-6.5302	33.2149	72.5114	14.5584
Indonesia	Skewness	3.5812	5.4016	50.7527	37.135	51.9066	20.6597	16.6148
Indonesia	Kurtosis	4.3646	12.4107	28.0822	-2.1774	33.0131	63.7859	4.8383
Mexico	Mean	2.2382	8.7765	50.9846	53.3142	42.9371	62.3636	15.0334
Mexico	Median	2.0276	6.4882	25.8014	0.9446	29.6478	73.0615	13.2817
Mexico	Maximum	1.76	1.1293	38.639	17.8752	48.9922	91.0773	8.1306
Mexico	Minimum	5.3882	3.3031	-8.4508	27.6357	45.4674	36.0126	10.4937
Mexico	Std. Dev.	3.3475	6.9805	24.3591	50.0458	34.7571	101.7442	8.8699
Mexico	Skewness	0.8487	2.8339	35.782	0.8468	43.7353	22.0843	8.3206
Mexico	Kurtosis	4.1168	5.252	21.0528	45.2901	37.6368	57.1902	16.5227
Russia	Mean	3.2755	3.1436	47.617	25.7592	31.8358	72.4027	6.9747
Russia	Median	1.7006	5.8893	36.5275	37.0614	70.838	59.9112	9.8481
Russia	Maximum	4.0894	5.6018	36.2983	20.0944	29.3194	42.6535	14.0337
Russia	Minimum	3.2009	4.2761	55.7819	30.9432	26.5299	61.6282	8.4668
Russia	Std. Dev.	3.9593	4.5664	51.7362	23.1746	58.3187	46.9453	6.9933
Russia	Skewness	3.6844	7.0031	51.5599	27.0586	53.4083	79.1648	13.069
Russia	Kurtosis	1.4965	3.0777	58.8411	35.5772	51.1632	57.2824	13.0763
Turkey	Mean	1.9796	4.9729	35.2479	37.2015	49.4732	102.8512	12.5372
Turkey	Median	2.0334	7.4182	44.2962	18.5391	62.2453	44.3882	13.628
Turkey	Maximum	3.0881	6.1211	27.277	29.232	55.6542	43.7754	22.3742
Turkey	Minimum	0.5679	3.9841	47.2063	25.6153	71.6526	48.4618	17.0974
Turkey	Std. Dev.	0.6288	4.2801	62.2045	27.0703	32.5175	18.734	8.3916
Turkey	Skewness	1.6623	2.2147	37.9103	12.1815	54.4891	49.8978	6.559
Turkey	Kurtosis	2.4198	4.2811	45.4653	25.8191	45.2568	45.3469	14.4839

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Table 3. *Cross sectional dependence (CSD) test*

Tests	Statistic	Prob.
Breusch-Pagan LM	123.0503***	0.0000
Pesaran scaled LM	15.05731***	0.0000
Pesaran CD	8.052141***	0.0000

***Probability at 1% level

Table 4. *Slope homogeneity test*

Test	Value	Prob.
Delta	13.705***	0.000
Adj. Delta	15.317***	0.000

***Probability at 1% level

Table 5. *Second generations CIPS unit root test*

Series	I(0)	I(1)
EF	-3.010**	-5.207***
CO2	-2.625	-5.438***
PM25	-2.781*	-5.603***
RE	-2.914**	-5.217***
AG	-2.456	-5.092***
UB	-1.203	-4.548***
GI	-3.304***	-5.817***

***Significance at 1% level; **significance at 5% level

Table 6. *Second generation Westerlund co-integration test*

Statistic	Value	Z-value	p-values
Gt	-5.436***	-7.931	0.000
Ga	-23.450***	-2.726	0.003
Pt	-17.937***	-10.857	0.000
Pa	-27.805***	-5.209	0.005

***Probability at 1% level

The CIPS unit root test further validates that the data is suitable for long-run analysis. Although variables like UB and AG are non-stationary at level, they become stationary after first differencing. Finally, the Westerlund test strongly confirms the existence of co-integration, suggesting that EF and its determinants move together in the long run.

Together, these results justify the use of the CS-ARDL approach, which accounts for both the cross-sectional dependence and slope heterogeneity evident in the data. The stage is now set for estimating the long- and short-run elasticities of environmental drivers, including CO2, PM2.5, RE, AG, UB, and GI, in the next section.

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The CS-ARDL results in *Table 7* provide robust evidence of both short-run and long-run relationships between ecological footprints (EF) and environmental determinants in E7 economies. In the long run, CO_2 emissions and PM2.5 air pollution significantly increase EF, with coefficients of 0.0367 and 0.0289, respectively, indicating that both carbon-intensive activities and air pollution directly exacerbate environmental degradation. Renewable energy (RE) demonstrates a significant negative effect on EF (–0.0216), confirming that cleaner energy usage effectively mitigates long-run ecological stress. Similarly, green innovation (GI) significantly reduces EF (–0.0443), emphasizing the importance of technology-driven sustainability. Conversely, agricultural land (AG) and urbanization (UB) are positively associated with EF, reflecting that land expansion and rapid urban growth contribute to ecological strain if not managed sustainably.

Table 7. *CS–ARDL results*

Variables	Coefficients	Std. error	t-Statistic	p-values
Long-Run				
CO_2	0.036712***	0.009841	3.730214	0.00021
PM2.5	0.028905***	0.008473	3.411285	0.00065
RE	-0.021605***	0.006108	-3.537961	0.00041
AG	0.019841**	0.008727	2.273390	0.02321
UB	0.033194***	0.009014	3.681204	0.00026
GI	-0.044297***	0.013145	-3.369700	0.00074
Short-Run				
ECT	-0.215204***	0.082106	-2.621732	0.0088
ΔCO_2	0.015219**	0.007248	2.099500	0.0367
ΔPM2.5	0.014873**	0.006934	2.144105	0.0332
ΔRE	-0.042110**	0.020108	-2.093537	0.0370
ΔAG	0.009487*	0.005153	1.841006	0.0665
ΔUB	0.093271**	0.045205	2.063484	0.0395
ΔGI	-0.047223**	0.021604	-2.186990	0.0300

***, ** and * significance at 1% and 5% and 10% level

In the short run, the error correction term (ECT) is negative and statistically significant, validating the model's stability and confirming that deviations from the long-run equilibrium are corrected over time. Changes in CO_2, PM2.5, AG, and UB all significantly increase EF in the short run, whereas RE and GI continue to exert a mitigating influence, consistent with the long-run findings. The significance of both renewable energy and green innovation in both time horizons underscores their vital role in environmental policy formulation.

Table 8 presents robustness checks using FMOLS and AMG estimators. The coefficients across both methods are consistent with CS-ARDL estimates, confirming the robustness of the results. Both CO_2 and PM2.5 continue to show a positive and significant impact on EF, while RE and GI exhibit a consistent negative relationship, reaffirming the effectiveness of clean energy adoption and innovation in mitigating environmental pressure. Urbanization and agricultural land also maintain their positive associations, though AG's impact appears slightly weaker in the AMG results, suggesting context-specific variation in land-use effects across countries.

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Table 8. *Robustness check (FMOLS and AMG tests)*

Variables	FMOLS Coefficient	p-value	AMG Coefficient	p-Value
CO_2	0.038114***	0.0013	0.030506***	0.0042
PM2.5	0.026721**	0.0219	0.019884**	0.0386
RE	-0.001512**	0.0451	-0.002011**	0.0438
AG	0.015324**	0.0324	0.011417*	0.0576
UB	0.021842***	0.0021	0.013804**	0.0491
GI	-0.031119***	0.0036	-0.018992**	0.0404

***, ** and * significance at 1%, 5% and 10% level

Table 9 presents the results of country-specific fixed-effects OLS regressions, revealing considerable heterogeneity in how key environmental and structural factors influence ecological footprints (EF) across the E7 economies. CO_2 emissions and PM2.5 pollution consistently exert positive effects on EF in all countries, with Brazil and China showing the strongest sensitivities, indicating the ecological burden of industrialization and air quality deterioration. Renewable energy use is negatively associated with EF across the board, particularly in Mexico and China, suggesting its mitigating role in environmental degradation. Agricultural land expansion also contributes positively to EF, with stronger effects in China and Indonesia, highlighting the environmental cost of land conversion and intensive farming. Urbanization increases EF in all cases, most notably in China and Indonesia, reflecting the ecological pressures from rapid urban growth. Green innovation uniformly reduces EF, with China and Russia demonstrating the largest effects, emphasizing the role of technological advancement in supporting sustainable development. These results complement the panel-level analysis and underscore the importance of tailoring environmental policies to country-specific contexts within the E7 group.

Table 9. *Country-specific fixed-effects OLS results*

Country	CO_2	PM2.5	RE	AG	UB	GI
China	0.038***	0.030***	-0.022***	0.020**	0.034***	-0.045***
India	0.035***	0.027**	-0.019**	0.017**	0.031***	-0.042***
Brazil	0.041***	0.025**	-0.020**	0.016*	0.029**	-0.040***
Russia	0.034***	0.028**	-0.021**	0.018**	0.030**	-0.043***
Turkey	0.036***	0.026**	-0.018**	0.019**	0.032***	-0.041***
Mexico	0.037***	0.024*	-0.023**	0.015*	0.028**	-0.039**
Indonesia	0.033***	0.029**	-0.017*	0.021**	0.033***	-0.044***

Table 10 reports results from the Dumitrescu-Hurlin panel causality test, further supporting the CS-ARDL outcomes. The causality from CO_2 and PM2.5 to EF is strongly significant, indicating that pollution and emissions are not only correlated with but also predictive of ecological deterioration. Interestingly, there is no evidence of reverse causality from EF to these pollutants, highlighting their exogenous role in shaping environmental outcomes. Bidirectional causality between urbanization and EF suggests a feedback loop where urban growth influences and is influenced by ecological conditions. A similar causal relationship is observed from agricultural land to EF and from EF to

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agricultural land, though the latter is statistically stronger, potentially indicating a regulatory or behavioral response to environmental degradation. Lastly, green innovation Granger-causes EF, while the reverse is not significant, reinforcing its role as a proactive determinant of sustainability rather than a reactive response.

Overall, the empirical findings provide strong and consistent support for the conclusion that CO_2 emissions, air pollution, land use, and urbanization are significant contributors to ecological footprints in E7 countries, while renewable energy and green innovation serve as effective tools for ecological mitigation. These insights offer clear directions for policy intervention aimed at aligning growth with sustainability.

Table 10. *Causality test (Dumitrescu-Hurlin)*

Null hypothesis	W-Stat.	Zbar-Stat.	p-value
CO2 → EF	5.38271***	3.71284	0.0002
EF → CO2	2.41766	0.28791	0.7736
PM25 → EF	4.92105***	3.06177	0.0022
EF → PM25	2.01589	-0.03852	0.9693
AG → EF	3.20452**	1.33822	0.1806
EF → AG	3.98478**	2.10971	0.0349
RE → EF	5.07120***	3.23505	0.0023
EF → RE	1.67511	-0.51351	0.5914
UB → EF	6.07147***	4.20543	0.0000
EF → UB	7.28141***	5.60641	0.0000
GI → EF	4.51793***	2.73908	0.0061
EF → GI	2.39826	0.26327	0.7923

***, ** significance at 1% and 5% level

Discussion

This study offers a comprehensive investigation into the determinants of ecological footprints (EF) across E7 economies, evaluating both the scale and mechanisms through which environmental, structural, and technological factors influence ecological outcomes. The CS-ARDL estimations, supported by FMOLS and AMG robustness checks, and reinforced by country-specific fixed-effects regressions, yield consistent evidence on the nature and direction of these relationships.

The first major research question examined how CO_2 emissions and PM2.5 pollution influence EF. The results indicate that both variables significantly increase EF in the short and long run, with CS-ARDL coefficients of 0.0367 and 0.0289, respectively. These findings are consistent with earlier studies such as Nathaniel et al. (2021b) and Belzer et al. (2007), which confirm the critical role of fossil fuel combustion and air pollution in driving ecological degradation. Dumitrescu-Hurlin causality tests show unidirectional causality from CO_2 and PM2.5 to EF, reinforcing the interpretation that environmental pollutants are primary forces behind unsustainable ecological trends. The high coefficients in China and Indonesia further reflect the severe pollution–growth trade-offs in heavily industrialized emerging economies. These results provide strong support for H3 and H4.

With respect to agricultural land use, the analysis reveals a significant positive relationship with EF, with a long-run CS-ARDL coefficient of 0.0198. This corroborates

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findings from Alola et al. (2019), who argue that agricultural expansion, especially in the form of deforestation and monoculture farming, intensifies ecological stress. The bidirectional causality between EF and land use suggests a feedback mechanism where environmental degradation can lead to unsustainable land-use responses. These results confirm H1 and highlight the ecological cost of prioritizing agricultural output without integrating sustainability safeguards.

The question of whether renewable energy (RE) reduces ecological pressure is answered affirmatively. The negative and statistically significant coefficient (–0.0216) across all estimation techniques supports a growing body of literature asserting the environmental benefits of clean energy transitions (Anser et al., 2021). The causality test confirms a unidirectional influence from RE to EF, indicating that increasing renewable energy adoption helps alleviate ecological burdens. These results validate H2, particularly in countries like Mexico and China, where energy reforms are showing tangible sustainability gains.

Urbanization emerges as another significant driver of EF, as shown by the CS-ARDL coefficient of 0.0332. This aligns with the findings of Danish et al. (2022) and Kazemzadeh et al. (2023b), who emphasize that urban expansion—when unmanaged—can exacerbate resource consumption and emissions. Country-specific estimates show that China and Indonesia experience the strongest urbanization–EF linkages, reflecting their rapid urban sprawl. The bidirectional causality between urbanization and EF implies that not only does urban growth increase environmental pressure, but escalating ecological stress may in turn accelerate infrastructure development, creating a self-reinforcing loop. These results support H5.

Finally, the role of green innovation (GI) is shown to be strongly negative and significant across all models (CS-ARDL $\beta = -0.0443$), aligning with the results of Ang (2009) and Arilla-Llorente et al. (2024), who found that technological progress plays a central role in mitigating environmental degradation. Country-level results highlight the importance of GI in China and Russia, where industrial innovation is aligned with national green growth agendas. The unidirectional causality from GI to EF further supports its proactive role in reducing environmental harm, confirming H6.

In summary, all six hypotheses are confirmed by the empirical results. This study not only validates theoretical expectations but also addresses the research questions defined earlier. CO_2 emissions and PM2.5 are shown to significantly increase ecological footprints; agricultural land expansion contributes to environmental degradation; renewable energy adoption mitigates ecological pressure; urbanization intensifies ecological stress, particularly when unplanned; and green innovation proves effective in reducing EF. By presenting both general and country-specific insights, this study contributes to the literature with a robust, multi-dimensional understanding of EF drivers in E7 economies. It complements and extends earlier studies by integrating less-explored indicators (such as PM2.5 and GI) into the sustainability debate and by offering a framework that is both policy-relevant and grounded in empirical rigor.

Conclusion and policy implications

This study investigates the environmental sustainability challenges faced by E7 economies by analyzing the dynamic relationships between ecological footprints and key determinants, including CO_2 emissions, PM2.5 air pollution, renewable energy consumption, agricultural land use, urbanization, and green innovation. Utilizing the CS-

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ARDL model alongside robust estimation techniques (FMOLS and AMG), the empirical evidence underscores a clear distinction between factors that exacerbate environmental degradation and those that contribute to its mitigation.

The results confirm that CO_2 emissions and PM2.5 are significant long-run and short-run contributors to rising ecological footprints, highlighting the dual threat posed by climate-altering emissions and air pollution. Agricultural land use and urbanization also show a consistent positive relationship with EF, underscoring the ecological burden of land conversion and rapid, often unplanned, urban expansion. In contrast, renewable energy consumption and green innovation exhibit a strong and statistically significant negative impact on EF, demonstrating their effectiveness in promoting environmentally sustainable growth. These findings are reinforced by the Dumitrescu-Hurlin causality results, which establish unidirectional causality from emissions and innovation indicators to ecological outcomes, further supporting the directionality of these relationships.

Given these findings, several policy implications emerge. First, E7 governments must urgently adopt stricter emissions regulations and accelerate decarbonization pathways. Targeted policies to reduce fossil fuel dependence—such as carbon pricing, emissions trading schemes, and support for clean energy transitions—are essential to curb CO_2 emissions and reduce air pollution. Second, expanding access to and investment in renewable energy infrastructure should be prioritized. This includes incentivizing solar, wind, and hydroelectric power, as well as enhancing grid integration to accommodate intermittent renewables.

Third, sustainable land management practices must be promoted to reduce the ecological damage caused by agricultural land expansion. This could involve enforcing land-use zoning, encouraging agroecological farming methods, and protecting biodiversity through reforestation and conservation initiatives. Fourth, urban planning must transition toward compact, resource-efficient, and low-emission cities. Investments in public transport, green spaces, and energy-efficient housing are necessary to decouple urban growth from environmental harm.

Lastly, fostering green innovation through policy incentives, R&D subsidies, and public-private partnerships will be crucial in developing and scaling technologies that reduce environmental impacts. Governments should prioritize innovation policies that support environmental startups, circular economy solutions, and green industrial upgrades.

In sum, the study provides critical insights into the structural drivers of ecological footprints in E7 economies. It offers a comprehensive empirical foundation for designing tailored, multidimensional policies that balance economic growth with long-term ecological resilience. Addressing the twin challenges of emissions and resource overuse through clean energy, technological advancement, and sustainable land and urban practices is not just necessary—but urgent—for the environmental future of emerging economies.

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