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Spatial Determinants and Spillover Effects of Carbon Emissions in SAARC Countries: Evidence from SAR, SEM, SDM, and SDEM Models

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Abstract

The South Asian Association for Regional Cooperation (SAARC) has been experiencing serious environmental consequences of rapid industrialisation, urbanisation and accelerating foreign direct investment (FDI) inflow. By considering the spatial interdependence of carbon emissions in the region, this research deploys a set of spatial econometric models (e.g., SAR, SEM, SDM and SDEM) on a balanced panel of 280 observations for eight SAARC countries over 1990-2024. The distance-based spatial weight matrices are used at two decay parameters ($\alpha = 1$ and $\alpha = 2$), for robustness check, within the threshold of 3,500 km. Lagrange Multiplier tests confirm significant spatial lag dependence (LM-Lag: 58.54, $p < 0.001$) in carbon emissions, justifying spatial modelling over standard OLS. A Pseudo $R^2 \approx 0.941$ and the lowest AIC values for both the SDM and SDEM confirm their superiority over counterparts (SAR and SEM). FDI is observed to be the most important source of carbon emissions, with its direct elasticity ranging from 1.63 to 2.30 across all specifications, supporting the pollution haven hypothesis (PHH). GDP per capita, carbon intensity of industry, and share of the urban population have sizeable positive direct impacts, while trade openness has a small negative effect on emissions. The results provide spatially disaggregated evidence favouring the development of South Asia's carbon abatement policies at a regional rather than national level. This includes screening of green FDI, industry-specific emission benchmarks, sustainable urban planning, and SAARC-level environmental cooperation agreements.

Keywords: *SAARC; Carbon Emissions; Spatial Econometrics; Spatial Spillover; Environmental Kuznets Curve; Pollution Haven Hypothesis.*

1. Introduction

The South Asian Association for Regional Cooperation (SAARC), encompassing Afghanistan, Bangladesh, Bhutan, India, Maldives, Nepal, Pakistan, and Sri Lanka, represents one of the world's most densely populated and rapidly industrialising regions. Collectively, these nations house over 1.9 billion people, and their aggregate economic output has expanded at annual rates exceeding 5-6 per cent since the mid-1990s (World Bank, 2024). This growth has been underpinned by accelerating urbanisation, large-scale industrial expansion, and a significant upswing in inward foreign direct investment (FDI). However, these achievements have come at a substantial environmental cost. The region's carbon dioxide (CO₂) emissions have risen sharply, driven by fossil-fuel-dependent energy systems, energy-intensive manufacturing, and rapid urban sprawl (United Nations Framework Convention on Climate Change [UNFCCC], 2024; International Energy Agency [IEA], 2023).

Thus, examining the drivers of carbon emissions in this region and their interactions across SAARC countries is highly policy-relevant. First, climate change directly endangers the livelihoods of the region's poorest populations, being associated with the risks related to extreme heat, irregular monsoon precipitation, rising sea-levels, and glacial melting (IPCC, 2022). Second, these challenges are tightly interlinked e.g., air pollution does not stop at national borders, shared watersheds, and growing regional economic integration suggest that countries' environmental policies have important spillover effects on their neighbours' economies (Gurjar et al., 2016). Moreover, recent empirical evidence suggests that the SAARC region is still in the rising phase of the Environmental Kuznets Curve (EKC), and that FDI and urbanisation continue to have positive impacts on emissions in South Asia (Sadiq et al., 2026; Akram et al., 2025; Padhan & Bhat, 2025).

Existing studies on the determinants of carbon emissions in SAARC have utilised conventional panel data methodologies, fixed effects, ARDL, VECM, and GMM estimators (Azam et al., 2022; Nur Mozahid et al., 2022; Mehmood, 2024), which assume that observations across cross-sectional units are independent of each other. This is econometrically invalid in the presence of spatial autocorrelation, and the violation of this assumption results in inconsistent and biased parameter estimates (Anselin, 1988). As a

result, the standard OLS diagnostic strongly rejects the adequacy of non-spatial estimators based on the presence of spatial lag dependence (Elhorst, 2014).

In other words, spatial econometrics offers a proper framework to deal with such dependencies. The Spatial Autoregressive (SAR) model accounts for the spatial lag of the dependent variable and can be used when emissions in one country are directly affected by those in its neighbours. The Spatial Error Model (SEM) accounts for spatial autocorrelation in the residuals arising from spatially structured shocks not included in the model. The Spatial Durbin Model (SDM) is an extension of the SAR model that includes spatial lags of the independent variables. The SDM can be decomposed into direct and indirect (spillover) effects (LeSage & Pace, 2009). The Spatial Durbin Error Model (SDEM) combines the lagged covariate structure of the SDM with spatially correlated errors.

Figure 1
Temporal-spatial Carbon Emission Comparison across SAARC Countries from 1990 to 2024

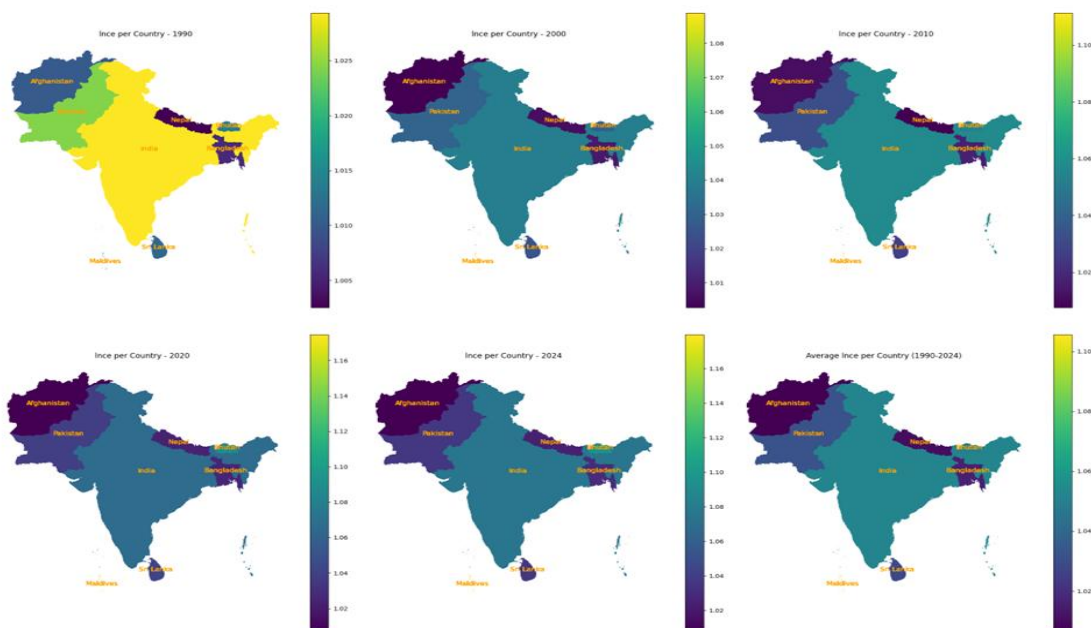
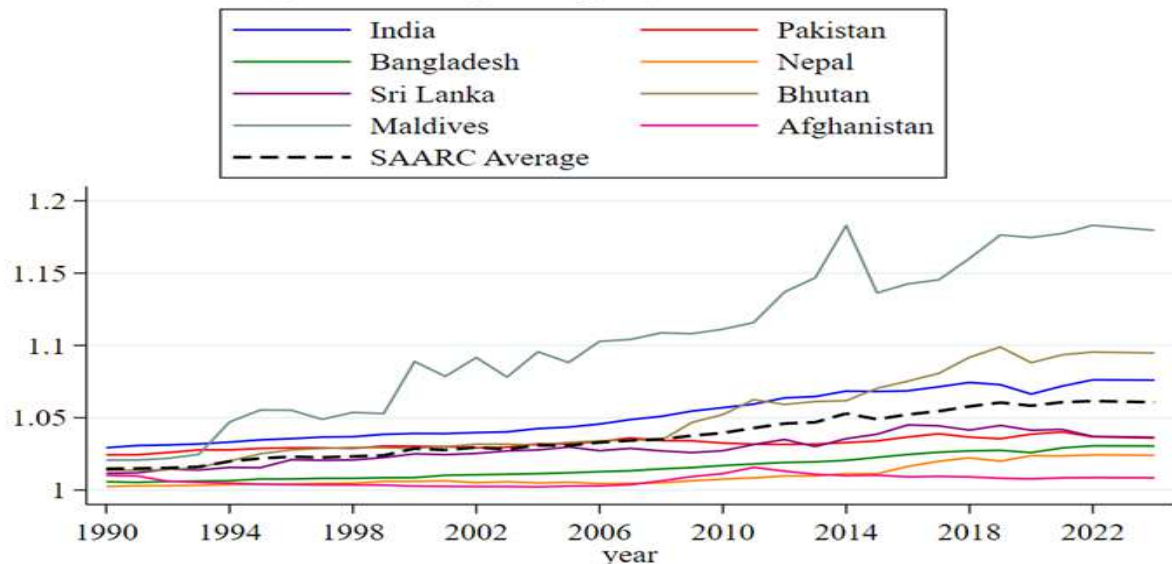


Figure 1 compares carbon emissions across SAARC countries over the years. Specifically, it shows the spatiotemporal distribution of average carbon emissions (CO_2) during 1990-2024. From this, one can conclude that across all the benchmark years, India's emission intensity is the highest and Bhutan, Nepal, and Maldives have the lowest emission levels. This emission is increasing over time in Bangladesh and Pakistan, but remains relatively stable in other SAARC countries. In terms of spatial distribution, the carbon emission level is very uneven

and increasing over the years, with a larger portion of emissions generated by a few countries rather than being evenly distributed across countries.

Figure 2
Carbon Emissions (Metric ton per capita) in SAARC Countries



The cross-country distribution of emissions in Figure 2 reveals a highly heterogeneous regional pattern of emission intensities across SAARC economies. Emissions from India are by far the highest in the region. This is followed by intermediate emission intensities for Pakistan and Bangladesh. Emissions from other smaller economies like Bhutan, Nepal and Maldives, are close to zero. The skewed distribution of emissions within SAARC reflects structural factors in industrialisation, energy consumption, and the size of the economy. The high concentration of emissions from a few large economies underlines the unevenness in environmental externalities within SAARC. In this sense, environmental outcomes at the regional level are primarily driven by a few larger economies in the region, which in turn are contingent on their developmental path. This asymmetry of emission sources and levels underlines a need for a more differentiated, yet concerted policy intervention in the context of environmentally intensive FDI-led industrial development.

Accordingly, this study contributes through applying the full suite of SAR, SEM, SDM, and SDEM specifications to a SAARC carbon-emissions panel dataset, enabling principled model selection. By covering 1990-2024, it provides the most temporally comprehensive spatial panel analysis of determinants of emissions in South Asia to date. Next, testing two spatial decay parameters ($\alpha = 1$ and $\alpha = 2$) provides evidence of systematic robustness. Finally, by

centring FDI within a spatial framework, it tests the pollution haven hypothesis (PHH) to provide guidance for (green) FDI governance in the region.

The rest of the study is organised as follows. Section 2 reviews the relevant literature. Section 3 reports on data, spatial weight matrices and econometric models. Section 4 demonstrates and discusses empirical results. Section 5 elaborates on conclusion and policy implications.

2. Literature Review

2.1 FDI and Carbon Emissions: The Pollution Haven-Halo Debate

The association between FDI and environmental quality rests at the core of international environmental economics and has generated an extensive and contested empirical literature. Two competing theoretical frameworks structure this debate. Pollution haven hypothesis (PHH) states that the corporations concerned with cost minimisation outsource environmentally intensive activities from their home countries to the host countries with weak environmental regulation, leading to an increase in emissions at the local level (Xing & Kolstad, 2002). On the contrary, the pollution halo hypothesis (PHE) argues that FDI provides the host countries with better technologies, cleaner production systems, and a more robust environmental management system, resulting reduced per-unit emissions at the local level (Demena & Afesorgbor, 2019).

Empirical evidence from South Asia has primarily supported PHH. Nur Mozahid et al. (2022) apply panel cointegration and Vector Error Correction Model (VECM) to SAARC countries for 1990-2016 and find that FDI inflows cause CO₂ emissions in the region, confirming the scale and composition effects of energy-intensive FDI, particularly in industry. Azam et al. (2022) observed similar results for the period up to 2018, by using the cross-sectional autoregressive distributed lag (CS-ARDL) and Pooled Mean Group (PMG) approaches, to conclude that FDI, GDP per capita, and industrial growth are jointly responsible for the surge in emissions. Balli et al. (2023) find similar results for Asia-Pacific Economic Cooperation (APEC) using the Common Correlated Effects Mean Group (CCEMG) estimator. Recently, Akram et al. (2025) confirm a direct positive link between FDI and carbon emissions, along with moderating effect of renewable energy adoption in this relationship, using non-linear ARDL for 1990-2018 in SAARC context. Worth noting is that pollution haven effect operates most strongly in lower-income economies, a finding directly relevant to SAARC, given its predominantly lower-middle-income composition.

The bilateral FDI dimension brings out further intricacies of the debate. Apergis et al. (2023) examine the PHH using bilateral FDI data from 11 OECD countries to the BRICS economies during 1993-2012, and find that the origin country of the FDI has a significant bearing on the direction of environmental impact, with FDI from countries having more stringent environmental regulations carrying the potential to result in cleaner technology adoption. On contrary, the counterpart from laxer environmental regimes tends to reinforce the pollution-intensive activity in the host economy. The bilateral frame of analysis would then be of additional salience to SAARC, which witnesses FDI not just from OECD economies but also from emerging Asian sources with heterogeneous environmental standards.

Li et al. (2023) provide the first study on the threshold-income dimension of the FDI-emissions nexus. Based on the panel threshold estimation for a sample of 67 countries, they find that FDI positively impacts carbon emissions if GDP per capita is lower than about \$541.87 and that the FDI emissions nexus at middle-income levels is not positive. This finding places SAARC economies, most of which remain below this threshold, squarely within the pollution-haven risk zone. Lin et al. (2022) provide a spatial perspective on this issue using Chinese provincial data, demonstrating that while FDI has a positive local effect on emissions (consistent with the PHH), its spatial spillover effect is negative. This suggests that emission-intensive production attracted by FDI in one province may displace such activities from neighbouring provinces. Such co-existence of the PHH and PHE in spatial terms directly motivates the spatial decomposition of FDI effects applied in the present study. In addition, Satoglu and Salmon (2025), in a 40-country panel (2010-2020), reassessing the PHH through the lens of environmental policy stringency. They observe that non-market-based and technology-support policies attract FDI, while moderating role of regulatory quality in FDI-emissions nexus complicates simple pollution-haven interpretations.

At sectoral level, Gong et al. (2025) demonstrates that the FDI-environment nexus is heterogeneous across the manufacturing, construction, and electricity generation sectors, with the construction sector particularly associated with pollution-haven effects in resource-rich economies. The sectoral heterogeneity further indicates that aggregate-level FDI regressions may mask the variation, and policies targeting particular types of investment (e.g., carbon-intensive manufacturing and energy infrastructure) are also advisable in SAARC countries.

2.2 Economic Growth, the EKC and South Asian Economies

Introduced by Grossman and Krueger (1995), EKC (an inverted-U relation between per capita income and environment degradation) remains one of the most widely tested hypotheses in environmental economics. The environmental degradation (e.g., emissions) increases with per capita income at low-income levels as a result of the scale effect. However, at higher levels of income, cleaner production technology and structural transformation to the service sector result in lower emissions. Thus, a turning point in the emissions-income relation occurs at a specific level of per capita income. South Asian countries, however, are consistently in the upward-sloping section of the EKC (with no turning point).

A study by Dua et al. (2024) on five South Asian economies finds that trade, FDI, and digitalisation all have aggregate effects on emissions, with economic growth having a consistently positive short-run impact on CO₂ emissions. Their study underscores that SAARC economies are firmly in the growth-intensive, emission-increasing phase of development. Likewise, Shafique et al. (2022) confirm the EKC's upward slope in South Asia using dynamic panel approaches, identifying urbanisation and energy consumption as main accelerants of emissions growth.

Global re-examinations of the EKC have moved well beyond simple inverted-U specifications. Wang et al. (2024) find that the EKC relationship in a global sample of 208 countries is better characterised as N-shaped (after explicit modelling of trade openness, human capital and renewable energy) than inverted-U and that the EKC turning point occurs at a global average GDP per capita of about \$19,200 (1990-2018). Of key relevance to the present study, they find that the emissions-reducing effect of human capital intensifies in post-EKC turning-point economies, while the emissions-mitigation effect of trade openness is statistically significant only in the post-turning-point sub-sample. Therefore, the behaviour of these (control) variables is heterogeneous across relative levels of economic development. This highlights the possibility that applying standard EKC estimates to lower-income SAARC economies may both be misspecified and re-examine the role of the control variables in the relationship, a motivation for the spatially-explicit multivariate framework.

Useful evidence in this regard comes from SAARC-specific studies, whereby Sadiq et al. (2026) employ a Panel ARDL model for eight member nations to address how economic growth is increasing the emission, while renewable energy and social entrepreneurship are reducing it. They reconfirm the region's EKC upward slope and the pivotal role of green

transition policies. Padhan and Bhat (2025), using a panel of five SAARC countries over 1995-2020, validate the inverted-U-shaped EKC for both ecological footprint and CO₂ emissions and show that social globalisation and institutional quality have a positive environmental influence. Mehmood (2024), using data from four South Asian countries between 1980 and 2019, documents that economic globalisation has increased carbon emissions in India, Pakistan, Sri Lanka, and Bangladesh. On the contrary, social and political globalisation has a positive but marginally insignificant effect on emissions reduction. Urbanisation and trade openness are net environment-degrading factors, in their sample. Consistent with this finding, the study of causative factors by Hussain et al. (2022), based on a panel of five South Asian countries, observes bi-directional Granger causality between urbanisation and CO₂ emissions, whereas a unidirectional causal link runs from GDP to emissions, reconfirming the EKC's location of SAARC economies on the upward slope.

2.3 Urbanisation, Trade openness and Industrial Structure

2.3.1 Urbanisation and Carbon Emissions

Urbanisation is one of the most structurally inelastic factors behind rising energy demand and carbon emissions in developing economies. The nexus between the industrial economy, residential energy consumption, transport infrastructure, and services that urbanisation underpins in the SAARC context has yielded strong, rising energy demand patterns that remain predominantly fossil fuel-based (Seto et al., 2014). Urban transport infrastructure alone is responsible for approximately 23 per cent of global energy-related CO₂ emissions (Qian, 2024), and rapidly urbanising South Asian cities are vulnerable to this trend.

Hussain et al. (2022), using the system-GMM estimator for the period 1990-2016, attempt to validate the bidirectional causality between urbanisation and emissions in South Asia. Teng et al. (2024), while analysing the urbanisation-transportation-industrialisation nexus in three major South Asian economies (China, India, and Indonesia), find that for every 1 per cent increase in GDP, per capita CO₂ emissions expand significantly. Moreover, urbanisation acts as an amplifying channel for industrial emissions rather than an independent driver. These findings have direct implications for SAARC, given the rapid urban population growth in Pakistan, Bangladesh, and Nepal (being fastest urbanising countries in the world) (United Nations Department of Economic and Social Affairs [UNDESA], 2023).

2.3.2 Trade Openness

Theoretical literature on the environmental impact of trade openness decomposes it into scale, composition and technique effects (Grossman & Krueger, 1995). The scale effect relates to increasing economic activity; thus, emissions follow an increase in trade; the composition effect with creation of new incentives shifting domestic production towards or away from pollution-intensive sectors; and the technique effect with the diffusion of cleaner technologies across borders. Empirically, the net direction of the relationship can be determined by the relative magnitude of the three effects and the ex-ante environmental regulatory regime of the trading economy.

In this respect, the evidence is mixed for South Asian economies. Mehmood (2024) finds that trade worsens environmental quality in the region, primarily through the scale and composition effects, as SAARC countries tend to export labour-intensive and energy-intensive goods while importing capital goods. Wang et al. (2024), however, find that trade openness has a significant negative effect on emissions in post-EKC turning-point countries, implying that the technique effect could eventually dominate with the development of SAARC economies. This forward-looking perspective is what this study attempts to check, by examining the extent to which current trade openness offsets domestic emissions through technology access and competitive efficiency pressures.

2.3.3 Human Development and Institutional Quality

Human capital and institutional quality exert their own environmental effects through pathways such as energy consumption patterns, environmental awareness, regulatory enforcement capacity, and the ability to absorb cleaner foreign technologies. Wang et al. (2024) demonstrate (across 208 countries) that human capital has a heterogeneous effect; a stronger emissions-reducing influence after the EKC turning point than before. For lower-income SAARC economies predominantly located on the EKC's upward slope, human development may initially correlate with higher emissions through the income-consumption pathway, before transitioning to a mitigating role at higher development levels.

Also, Abdouli and Omri (2021) report that FDI, human capital, and environmental quality interact non-linearly across Mediterranean economies, with human capital eventually moderating the emissions impact of FDI. Padhan and Bhat (2025) confirm in SAARC context that institutional quality reduces CO₂ emissions, reinforcing the importance of governance capacity in the emissions-development nexus. This non-linear and context-dependent

dynamics is to be captured in finding the way human development (MHDI) exhibits a sign reversal across model families.

2.4 Spatial Econometric Approaches in Environmental Research

2.4.1 Global and Regional Studies

The application of spatial econometric methods to environmental research has accelerated substantially since Anselin's (1988) foundational work on spatial econometrics methods and models. LeSage and Pace (2009) provide the canonical decomposition of spatial effects into direct and indirect components, which is central to the SDM and SDEM frameworks employed here. Elhorst (2014) extends the spatial panel toolkit to fixed- and random-effects specifications that are directly applicable to multi-country panels, as used in this study.

Zhang et al. (2023) apply the spatial Durbin model to examine carbon emission efficiency in RCEP (Regional Comprehensive Economic Partnership) member states, finding significant positive spatial autocorrelation in efficiency. They confirm that technological diffusion and industrial structure create cross-country spillovers that conventional panel models miss. The dynamic spatial Durbin model (DSDM) applied by Dabbous et al. (2024) to 135 countries confirms that the indirect spillover effects of energy consumption on CO₂ emissions are significant and non-negligible, and that neighbouring countries' energy choices materially affect domestic environmental outcomes. This finding is believed to be having strong relevance for the energy-interdependent SAARC region.

The simultaneous application of SAR, SEM, and SDM to enable model comparison is advocated by Elhorst (2014) on the grounds that the appropriate spatial specification is an empirical question that cannot be resolved a priori. Jeetoo (2023) follows this approach in Sub-Saharan Africa, applying the SDM to test both the EKC and PHC simultaneously, demonstrating that spatial modelling substantially changes the estimated elasticities relative to non-spatial estimators. Mahmood (2023) uses the SDM on 18 Latin American countries to show that FDI has a positive direct effect on emissions alongside significant spatial spillovers through trade and production linkages, a structural parallel to the SAARC configuration analysed by this study.

2.4.2 South Asia-Specific Spatial Studies and Research Gap

Despite the rapid global growth of spatial environmental econometrics, the application in South Asia remains underdeveloped. Also, the existing SAARC-focused literature has largely

relied on first-generation panel techniques. For example, Azam et al. (2022) use CS-ARDL and PMG but do not account for spatial spillovers. Nur Mozahid et al. (2022) employ VECM to capture temporal dynamics but cannot detect cross-country emission propagation. The globalisation and emissions study of Mehmood (2024) uses FGLS estimation for a subset of four South Asian countries, which corrects for serial correlation but not spatial correlation. Likewise, Dahal et al. (2024) examine the globalisation-emissions nexus across South Asia by employing panel FGLS without spatial weight matrices. Akram et al. (2025) and Sadiq et al. (2026) advance the SAARC literature but still rely on non-spatial cointegration methods. These methodological gaps are particularly consequential given SAARC's unique spatial characteristics; a region dominated by one very large economy (India) surrounded by much smaller neighbours, creating pronounced spatial heterogeneity in emissions levels, industrial structure, and policy capacity. By considering that no prior study has applied the full model hierarchy, nor has systematically compared goodness-of-fit across SAR, SEM, SDM, and SDEM specifications for SAARC region, this paper provides a comprehensive spatial econometric analysis of carbon emissions to date.

Table 1 provides a summary of the major studies conducted in the region, along with their methodologies and key findings, to help identify gaps for the current study.

Table 1
Literature Review Summary: Summary of Key Prior Studies and Methodological Positioning

Study	Region	Period	Method	Key Finding	Gap Addressed
Nur Mozahid et al. (2022)	SAARC	1990-2016	VECM, DOLS	FDI drives CO ₂ emissions; unidirectional GDP → CE causality	No spatial spillovers modelled
Azam et al. (2022)	SAARC	1990-2018	CS-ARDL, PMG	Urbanisation, GDP, energy, FDI all increase CO ₂	No spatial weight matrices; pooled estimates
Balli et al. (2023)	APEC	1981-2021	CCEMG	FDI negatively affects air quality (PHH)	SAARC not covered; no spillover decomposition
Apergis et al. (2023)	BRICS	1993-2012	Panel, bilateral FDI	FDI origin country matters for CO ₂ outcomes	No spatial econometrics; SAARC absent
Mahmood (2023)	Latin America	1970-2019	SDM	PHH validated; spatial spillovers significant via trade	Different region; no SDEM/GNS comparison
Zhang et al. (2023)	RCEP	Unspecified	SDM, Moran's I	Significant spatial autocorrelation in emission efficiency	Not SAARC; focused on efficiency not levels
Lin et al. (2022)	China provinces	2004-2015	SDM	PHH locally, PHE spillover - co-existence	Sub-national; not applicable to multi-country SAARC
Mehmood (2024)	South Asia (4)	1980-2019	FGLS	Economic globalisation raises CO ₂ ; PHH for FDI component	Only 4 countries; no spatial weight matrix
Jeetoo (2023)	Sub-Saharan Africa	2002-2015	SDM	SDM captures PHH and EKC not detectable in OLS	Africa focus; no SDEM or GNS; different geography
Akram et al. (2025)	SAARC	1990-2018	NARDL	FDI positively related to CE; renewables moderate it	Non-spatial; no spillover decomposition
Padhan & Bhat (2025)	SAARC (5)	1995-2020	DK-SEs, FMOLS	Institutional quality and social globalisation lower CO ₂	No spatial model; only 5 of 8 countries
Sadiq et al. (2026)	SAARC (8)	Unspecified	Panel ARDL	Growth drives emissions; renewables reduce them	Non-spatial; no cross-border spillovers

Present Study	SAARC (8)	1990-2024	SAR, SEM, SDM, SDEM	Full spatial model hierarchy; PHH confirmed; SDM/SDM superior; FDI dominant driver	First comprehensive multi-model spatial panel for SAARC
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Note: CCEMG = Common Correlated Effects Mean Group; FGLS = Feasible Generalised Least Squares; NARDL = Non-linear ARDL; DK-SEs = Driscoll-Kraay Standard Errors; PHH = Pollution Haven Hypothesis. *Source:* Author's Creation

3. Data and Methodology

3.1 Data

The study uses an annual balanced panel of 280 observations of eight member countries of the SAARC (Afghanistan, Bangladesh, Bhutan, India, Maldives, Nepal, Pakistan, and Sri Lanka) over the period 1990-2024. The dependent variable is carbon emissions (CE), in log metric tonnes of CO₂ per capita, collected from National Inventory Reports of the United Nations Framework Convention on Climate Change (UNFCCC, 2024) and the World Bank's World Development Indicators (WDI, 2025). All the variables are taken in natural logs to interpret the elasticities directly and to reduce heteroskedasticity. Table 2 displayed descriptive statistics.

Table 2

Descriptive Statistics of Panel Variables

Variable	Mean	Std. Dev.	Min	Max	Description
CE	1.038	0.038	1.002	1.183	Log CO ₂ emissions per capita
IFDI	2.006	0.010	1.981	2.061	Log inward FDI (% of GDP)
GDP	3.124	0.405	2.456	4.042	Log GDP per capita (constant USD)
MHDI	1.685	0.185	1.000	2.041	Log modified HDI (Education component-adjusted)
UPTOP	1.558	0.100	1.275	1.740	Log urban population (% of total)
CC	1.998	0.003	1.993	2.007	Log industrial carbon intensity index
TOP	1.879	0.506	1.191	3.707	Log trade openness (trade/GDP ratio)

Note: All variables log-transformed. Sources: World Bank WDI (2025), UNFCCC (2024), IEA (2026). *Source:* Author's Creation.

The six independent variables are: inward FDI inflows (% of GDP) (FDI), GDP per capita (constant 2015 USD\$) (GDP), modified Human Development Index adjusted by Education intensity (MHDI), urban population (% of total population) (UPOP), control of corruption (CC), and trade openness (imports and exports as % of GDP) (TOP). These variables reflect the main economic, demographic, and

Figure 3

Spatial connection (3500 km Distance Band)



institutional transmission channels through which carbon emissions (CE) evolve in the SAARC development process.

3.2 Spatial Weight Matrices

For our distance-based spatial weight matrices, we used Euclidean distances between country centroids, setting a 3,500 km threshold for the distance band (see Figure 3). This latter threshold yields connected components that include all eight SAARC countries, with a mean of 227.5 neighbours per observation. In order to explore the role of spatial decay, we evaluate two inverse-distance power functions:

$\alpha = 1$ (gradual decay as inverse distance):

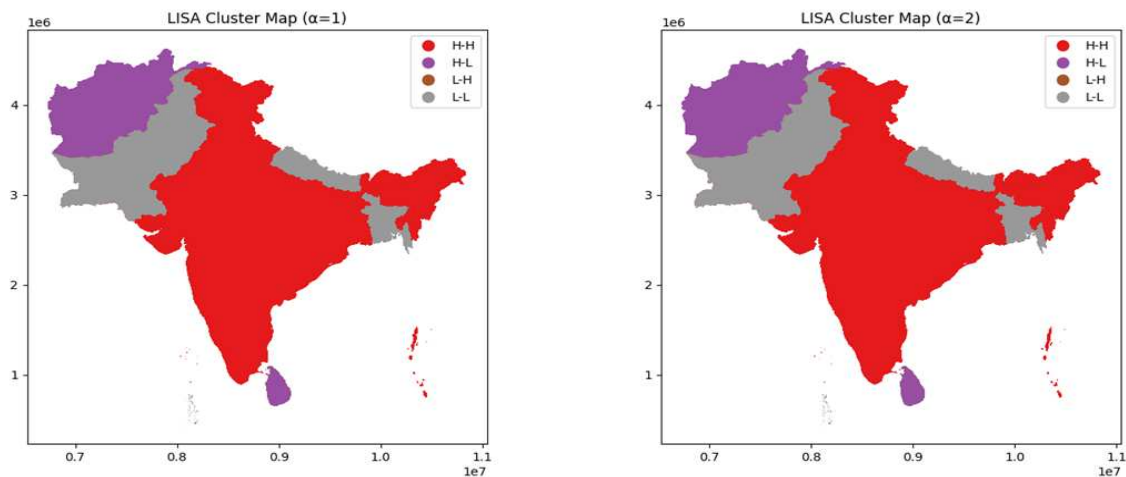
$$W_{ij} = \begin{cases} \frac{1/d_{ij}}{\sum_j (1/d_{ij})}, & \text{if } d_{ij} \leq d_{threshold} \\ 0, & \text{otherwise} \end{cases}$$

$\alpha = 2$ (steeper decay as inverse squared distance):

$$W_{ij} = \begin{cases} \frac{1/d_{ij}^2}{\sum_j (1/d_{ij}^2)}, & \text{if } d_{ij}^2 \leq d_{threshold} \\ 0, & \text{otherwise} \end{cases}$$

Where (W_{ij}) is the spatial reach of country (j) over country (i), and ($d_{threshold}$) is the distance threshold (tested for 3500 km). Both matrices are row-standardised so that spatial lags are weighted averages of neighbouring values to make coefficients more comparable (LeSage and Pace, 2009). Estimating the model with $\alpha = 1$ and $\alpha = 2$ constitutes a direct robustness test of the results' sensitivity to the assumed distance-decay function.

Figure 4
LISA plots



The maps of the LISA cluster (for spatial weight matrix $\alpha = 1$ and $\alpha = 2$) depict similar patterns of clustering and dispersion. This suggests spatial clustering of high and low FDI values, with evidence of a competitive spatial dispersion effect in the FDI performance of SAARC countries (Figure 4). India is the only economy included in the high-high (H-H) category, while other economies such as Afghanistan and Nepal consistently fall into the low-low (L-L) cluster. The observed presence of high-low (H-L) and low-high (L-H) combinations in some countries can be attributed to asymmetric spatial interaction, with some economies outperforming their neighbours and others adversely affected by their high-performing neighbours. The observation that clustering patterns in LISA maps remain largely similar, under both $\alpha = 1$ and $\alpha = 2$, suggests the robustness of spatial dependence to alternative specifications of distance-decay assumptions. Furthermore, the overall clustering pattern (of LISA) supports a structurally uneven regional investment landscape with a concentration of high FDI values in larger economies and a lack of spillover to their lagging neighbouring economies.

Global Moran's I provide empirical justification for spatial modelling and confirm any significant spatial autocorrelation in CE under both specifications. Consistent with SAARC's structural heterogeneity, the negative Moran's I values indicate a checkerboard pattern; high-emission economies (e.g., India) bordered by lower-emission neighbours (Nepal, Bhutan, Maldives).

3.3 Diagnostic Testing

Before model estimation, several diagnostic procedures are conducted. Following Pesaran (2004), we run the Cross-sectional Dependence (CD) test to investigate the presence of cross-sectional dependence across the panels. A sequence of panel unit root tests is performed: the Levin-Lin-Chu (2002) and Im-Pesaran-Shin (2003) first-generation tests (for reference), and the second-generation Pesaran (2007) CIPS test being the main stationarity check (Table 4). Since the orders of integration are mixed ($I(0)$ and $I(1)$), Kao (1999), Pedroni (1999), and Westerlund (2007) panel cointegration tests are conducted to check the existence of long-run relationships (Table 5). The Hausman test ($\chi^2(6) = 115.09$, $p < 0.001$) allows us to retain the fixed-effects panel specification over the random-effects specification (Table 7). Lagrange Multiplier (LM) tests for the inclusion of spatial dependence can distinguish between a spatial process entering through the dependent variable and the one entering through the error structure.

3.4 Econometric Models

Four spatial panel specifications are estimated via maximum likelihood with individual fixed effects, enabling principled model selection through goodness-of-fit criteria.

Spatial Autoregressive Model (SAR):

$$CE_{it} = \rho WCE_{it} + \beta X_{it} + \epsilon_{it}$$

where ρ captures the spatial lag in the dependent variable (carbon emissions). A significant ρ indicates emission spillovers across borders.

Spatial Error Model (SEM):

$$CE_{it} = \beta X_{it} + \mu_{it}, \quad \mu_{it} = \lambda W\mu_{it} + \epsilon_{it}$$

where λ captures spatial autocorrelation in unobserved disturbances such as regional climate shocks or correlated institutional quality.

Spatial Durbin Model (SDM):

$$CE_{it} = \rho WCE_{it} + \beta X_{it} + \theta WX_{it} + \epsilon_{it}$$

Here, extending SAR with spatially lagged covariates to enable direct (local)/indirect (spillover) effect decomposition. WX_{it} denotes spatially lagged covariates capturing the influence of neighbours' characteristics on domestic CE (carbon emissions) and θ is the coefficient of neighbouring characteristics.

Spatial Durbin Error Model (SDEM):

$$CE_{it} = \beta X_{it} + \theta WX_{it} + \mu_{it}, \quad \mu_{it} = \lambda W\mu_{it} + \epsilon_{it}$$

Combining spatially lagged covariates with spatially correlated errors- the most general specification in this study.

Model selection relies on Pseudo R^2 , log-likelihood, AIC, and SIC. The preferred model is identified as the specification with the lowest AIC and highest log-likelihood. This decision criterion follows Elhorst (2014) and is consistent with the approach of Zhang et al. (2023) and Dabbous et al. (2024) in comparative spatial model selection.

3.5 Effect Decomposition

Following LeSage and Pace (2009), the SDM coefficient vector cannot be interpreted directly as marginal effects because each variable's spatial lag generates feedback effects across all

spatial units. The total impact of each determinant is decomposed into three interpretable components:

- i) Direct effects- the impact of a variable in country i on its own carbon emissions (sum of diagonal elements of the impact matrix);
- ii) Indirect effects- spillovers from neighbours' characteristics on country i 's carbon emissions (average of off-diagonal elements); and
- iii) Total effects- the sum of direct and indirect components, representing the full influence on the spatial system.

$$\text{Total Effect} = (I - \rho W)^{-1}(X\beta + WX\theta)$$

All models are estimated by Maximum Likelihood (ML). Robustness is assessed across both $\alpha = 1$ and $\alpha = 2$ spatial specifications, evaluating the stability of findings under different assumptions about spatial decay.

4. Empirical Results

4.1 Diagnostic Tests

Table 3.
Pair-wise Correlation Matrix

Variables	1	2	3	4	5	6	7
(1) CE	1.000						
(2) FDI	0.789	1.000					
(3) GDP	0.802	0.652	1.000				
(4) MHDI	0.693	0.451	0.738	1.000			
(5) CC	0.344	-0.054	0.349	0.361	1.000		
(6) TOP	0.185	0.372	0.291	-0.125	0.023	1.000	
(7) UPOP	0.628	0.363	0.463	0.414	0.133	0.0001	1.000

Notes: Variables numbered (1)- (7) as in rows. All correlations computed from log-transformed variables across 280 observations (8 countries $\times$ 35 years) and are significant at 0.01 level. *Source:* Author's creation.

Table 4.
Pesaran (2007) CIPS Panel Unit Root Test Results

Variable	CIPS Statistic	10% CV	5% CV	1% CV	Decision	Integration Order
FDI	-3.568	-2.73	-2.84	-3.06	Stationary	I(0)
GDP	-2.743	-2.73	-2.84	-3.06	Borderline	I(1)
d.GDP	-4.186	-2.73	-2.84	-3.06	Stationary	I(1) confirmed
CE	-2.551	-2.73	-2.84	-3.06	Non-stationary	
d.CE	-5.112	-2.73	-2.84	-3.06	Stationary	I(1) confirmed
MHDI	-3.627	-2.73	-2.84	-3.06	Stationary	I(0)

CC	-3.052	-2.73	-2.84	-3.06	Stationary	I(0)
TOP	-1.526	-2.73	-2.84	-3.06	Non-stationary	
d.TOP	-4.811	-2.73	-2.84	-3.06	Stationary	I(1) confirmed
UPOP	-0.114	-2.73	-2.84	-3.06	Non-stationary	
d.UPOP	-4.841	-2.73	-2.84	-3.06	Stationary	I(1) confirmed

Notes: CIPS = Cross-Sectionally Augmented IPS test. Estimated with constant and trend (maxlags(2), bglags(1)). Critical values: 10% = -2.73; 5% = -2.84; 1% = -3.06. H_0 : all panels contain a unit root. d. and d2. denote first and second differences. *Source:* Author's creation.

Table 3 shows pair-wise correlation matrix, whereby all the correlations appeared to be significantly ($p < 0.01$). Carbon Dioxide (CO₂) emissions correlate strongly with FDI ($r = 0.789$) and GDP per capita (0.652). Control of corruption is negatively correlated with FDI ($r = -0.054$), giving an early hint of the perverse institutional finding.

Pesaran (2004) CD tests show that all variables exhibit significant cross-sectional dependence ($p < 0.05$), indicating towards the appropriateness of second-generation panel methods. Table 4 provides the CIPS panel unit root results. The dependent (CE), trade openness (TOP), and urban population (UPOP) variables are I(1); GDP per capita also requires first differencing; and the rest of the series are stationary in levels (FDI, MHDI, and CC). This mixed-order integration shows the validity of spatial panel framework with robust standard errors over the ordinary least squares (OLS) and standard panel cointegration methods.

Table 5 presents panel cointegration test results. All applied tests: Kao (1999), Pedroni (1999), and Westerlund (2007), confirm long-run cointegration among the variables ($p < 0.05$), validating the estimation of long-run spatial panel models.

Table 5.
Panel Cointegration Test Results

Test	Null Hypothesis	Statistic	p-value	Decision
Kao (1999)	No cointegration	-11.476	0.000	Cointegration confirmed
Pedroni PP-t (same AR)	No cointegration	-8.686	0.000	Cointegration confirmed
Pedroni ADF-t (same AR)	No cointegration	-9.213	0.000	Cointegration confirmed
Pedroni PP-t (panel-specific)	No cointegration	-8.029	0.000	Cointegration confirmed
Westerlund (some panels)	No cointegration	-2.613	0.005	Cointegration confirmed
Westerlund (all panels)	No cointegration	-1.972	0.024	Cointegration confirmed

Notes: All tests include individual intercepts, deterministic trends, and cross-sectional mean removal. Westerlund (2007) robust to cross-sectional dependence. Pedroni (2004) allows heterogeneous cointegrating vectors. H_0 : no cointegration.

Source: Author's creation.

Table 6 presents the spatial diagnostics. Moran's I values are negative and highly significant for emissions (CE) under both $\alpha = 1$ (-0.045, $p < 0.001$) and $\alpha = 2$ (-0.053, $p < 0.001$), confirming the presence of spatial dependence. This also indicates that SAARC's spatial structure, high-emission large economies bordered by lower-emission smaller ones, creates systematic cross-country patterns that non-spatial models misattribute to country-specific factors.

Critically, the Robust LM-Lag statistic (51.87, $p < 0.001$) remains highly significant after correction for spatial error dependence, while the non-significant Robust LM-Error statistic (2.63) unambiguously recommends the SAR/SDM family over the SEM as the appropriate spatial specification.

Together, these tests confirm the presence of spatial dependence in the dependent variable (CE), not in the error structure. In other words, CO₂ emissions in one SAARC country are significantly influenced by emissions in other neighbouring countries, indicating regional spillovers in pollution dynamics associated with shared borders, trade, and energy systems.

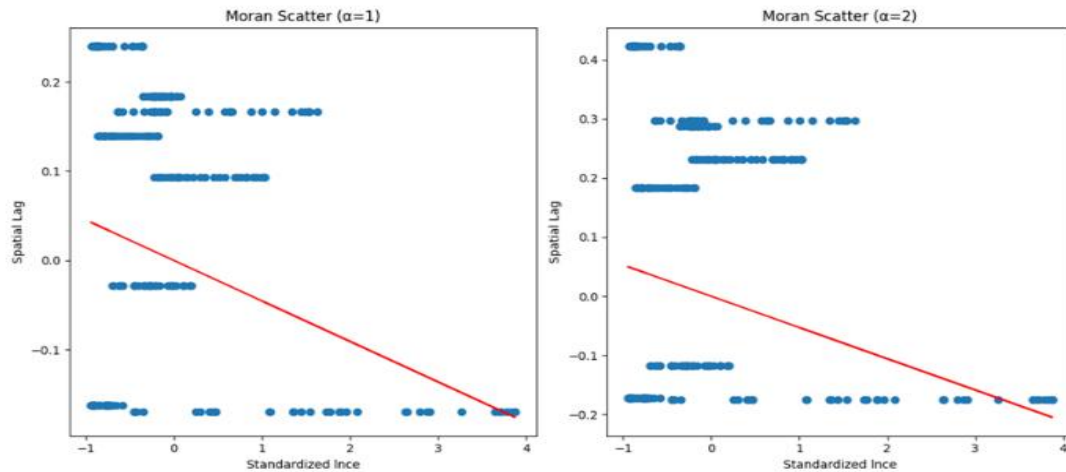
Table 6.
Spatial Dependence Diagnostics

Test / Specification	Statistic	p-value	Implication
Moran's I (CE, $\alpha=1$)	-0.0453	0.0010	Negative spatial autocorrelation
Moran's I (CE, $\alpha=2$)	-0.0528	0.0010	Spatial dependence confirmed
LM-Lag	58.5360	0.0000	Highly significant → indicates spatial lag dependence. CO ₂ emissions in one country depend on neighbouring countries' emissions.
LM-Error	9.2960	0.0023	Significant → spatial autocorrelation in residuals. Omitted spatial processes likely exist.
Robust LM-Lag	51.8723	0.0000	Still significant after adjusting for spatial error correlation → confirms a spatial lag process.
Robust LM-Error	2.6323	0.1047	Not significant after controlling for lag dependence → indicates that the main spatial dependence is lag-type, not residual-based.

Notes: Moran's I is based on residuals from a traditional panel OLS regression (the spatial weight matrix is distance-based, with a threshold of 3,500 km). LM tests are used to differentiate between spatial lag and spatial error specifications. p-values are based on 999 Monte Carlo permutations. *Source:* Author's creation

In addition to the negative coefficient estimates, the Moran scatter plots for both the spatial specifications ($\alpha = 1$ and $\alpha = 2$) show a negative spatial autocorrelation (downward slope of the fitted lines) in the cross-country pattern of FDI across SAARC (Figure 5). This is characterised by neighbours tending to exhibit significantly different patterns of FDI inflows. The negative slope coefficient in the fitted line indicates that countries with high levels of FDI tend to have neighbours with low FDI and vice versa, with the distribution of observations across quadrants (notably the prevalence of high-low and low-high configurations) providing further evidence of competitive spillovers among neighbours. Moreover, since this pattern is found for both weighting schemes, we can rule out the possibility that the spatial structure of FDI in SAARC is a function of an alternative specification of distance decay.

Figure 5
Moran scatter Plot for moth matrices



4.2 Baseline OLS and Spatial Diagnostics

Table 7 reports OLS ($R^2 = 0.898$) estimates and LM spatial diagnostic tests. FDI ($\beta = 2.186$, $p < 0.001$), CC ($\beta = 3.037$, $p < 0.001$), and UPOP ($\beta = 0.101$, $p < 0.001$) are appeared to be the main driving forces of carbon emissions. However, TOP ($\beta = -0.005$, $p < 0.01$) has a small emissions abating effect, in line with the technique effect of globalisation. The Hausman test ($\chi^2(6) = 115.09$) confirms the appropriateness of fixed effects. The Breusch-Pagan test ($\chi^2(6) = 166.39$, $p < 0.001$) confirms the presence of heteroskedasticity. In general, these OLS baseline results are broadly in line with the Azam et al. (2022) and Nur Mozahid et al. (2022) for a similar SAARC sample. Though the robust LM tests unambiguously confirm the spatial lag dependence, thus recommending the SAR/SDM family as the preferred specification.

Table 7
OLS Baseline Regression and Lagrange Multiplier Spatial Diagnostics

Variable / Test	Coefficient / Statistic	Std. Error	t / z / χ^2	p-value
Constant	-9.643	0.668	-14.43	0.000
FDI	2.186	0.109	20.02	0.000
GDP	0.014	0.004	3.70	0.000
MHDI	0.023	0.007	3.26	0.001
CC	3.037	0.279	10.89	0.000
TOP	-0.005	0.002	-2.67	0.008
UPOP	0.101	0.008	12.01	0.000
Model Diagnostics				
R-squared	0.898			
Hausman Test	$\chi^2(6) = 115.09$			0.000 → FE preferred

Note: $N = 280$, 8 SAARC countries, 1990–2024. Dependent variable: CE (log CO_2 emissions per capita).
Source: Author's Creation

4.2 SAR Model Results

Table 8
SAR Model Estimates and Impact Decomposition

Variable	$\alpha = 1$	$\alpha = 2$
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	Coeff.	Direct	Indirect	Coeff.	Direct	Indirect
FDI	2.151***	2.151	-0.541	2.194***	2.194	0.282
GDP	0.014***	0.014	-0.004	0.014***	0.014	0.002
MHDI	0.020**	0.020	-0.005	0.024***	0.024	0.003
CC	3.232***	3.232	-0.813	2.921***	2.921	0.375
TOP	-0.008**	-0.008	0.002	-0.004†	-0.004	-0.001
UPOP	0.101***	0.101	-0.026	0.100***	0.100	0.013
ρ (W_CE)	-0.336†			0.114 (ns)		
Pseudo R ²	0.899			0.898		
Log-Likelihood	842.39			841.65		
AIC	-1668.78			-1667.30		

Note: *** p<0.001; ** p<0.01; † p<0.10; ns = not significant. Impacts via 'simple' method. Source: Author's Creation

Table 8 presents SAR estimation results. Pseudo R² of 0.899 ($\alpha = 1$) and 0.898 ($\alpha = 2$) are reasonably high. Spatial lag parameter $\rho = -0.336$ ($p = 0.090$) under $\alpha = 1$ indicates modest negative spatial autocorrelation, supporting the structure of SAARC, which features India as a high-emission economy having many smaller low-emission neighbours. Under $\alpha = 2$, $\rho = 0.114$ ($p = 0.380$) is statistically insignificant, reflecting the diminishing of direct emission spillovers over longer distances. Control of corruption has the significantly ($p < 0.001$) largest positive direct effect (ranging 3.23-2.921), followed by that of FDI (2.15-2.19) and UPOP (0.101-0.100). The negative direct effect of trade openness (TOP) is robust to both distance specifications.

4.3 SEM Model Results

For the SEM, the spatial error parameter $\lambda = -0.997$ ($p < 0.05$) for $\alpha = 1$ and $\lambda = -0.915$ ($p < 0.01$) for $\alpha = 2$ is found significant and negative (Table 9). This means that unobserved spatial shocks, regional climate events, correlated infrastructure investment cycles or shared policy announcements are negatively autocorrelated across neighbouring SAARC countries. The negative λ indicates that positive unobserved shocks in a country will be, on average, partially offset by unobserved shocks in neighbouring countries. The SEM coefficients for all substantive regressors are relatively similar to that in OLS and SAR baselines, with the former (SEM) providing strong cross-model robustness for all major results. SEM has marginally higher log-likelihood (843.56 vs 842.39 for $\alpha = 1$) and lower AIC (-1673.11 vs -1668.78) than SAR, confirming that unobserved spatial heterogeneity is an additional source of explanatory power.

Table 9
SEM Model Estimates

Variable	$\alpha=1$ Coeff	St. Err	z-stat	p-value	$\alpha=2$ Coeff	St. Err	z-stat	p-value
Constant	-9.842	0.716	-13.74	0.000	-9.878	0.713	-13.86	0.000
FDI	2.163	0.108	20.03	0.000	2.187	0.107	20.36	0.000
GDP	0.013	0.004	3.71	0.000	0.013	0.004	3.63	0.000
MHDI	0.022	0.007	3.02	0.003	0.026	0.007	3.61	0.000
CC	3.160	0.313	10.09	0.000	3.153	0.312	10.11	0.000
TOP	-0.005	0.002	-2.61	0.009	-0.004	0.002	-2.18	0.029
UPOP	0.102	0.009	11.53	0.000	0.098	0.009	11.36	0.000
λ (Lambda)	-0.997*	0.453	-2.20	0.028	-0.915**	0.301	-3.04	0.002

Pseudo R ²	0.898	0.898
Log-Likelihood	843.56	842.55
AIC	-1673.11	-1671.10

Note: Dependent variable: CE. St. Err is Standard Error. Coeff is Coefficient.
Source: Author's Creation

4.4 SDM Model Results and Spillover Decomposition

The SDM has a Pseudo R² of 0.941 ($\alpha = 1$) and AIC of -1808.05, dwarfing those for SAR and SEM. Table 10 displays the full direct/indirect/total effect decompositions. Under $\alpha = 1$, the direct effect of FDI is 1.633, with an indirect (spillover) effect of -0.039. The direct effect indicates that FDI strongly raises domestic emissions, but holds a weak spillover that dampens emissions in contiguous countries. This spatial coexistence of PHH locally and PHE regionally was also observed by Lin et al. (2022) in the context of China. The control of corruption (CC) has the largest direct effect (5.931) and a small negative indirect effect (-0.143) to confirm that highly effective governance activity is driven and working at home. Human development (MHDI) has a negative direct effect of -0.054 ($p < 0.001$) in the SDM, which is consistent with Wang et al. (2024), demonstrating that human capital development reduces emissions once spatially lagged covariates have soaked up regional covariation. Urban population (UPOP) is significant under $\alpha = 1$ but not under $\alpha = 2$, confirming that the footprint of urbanisation is local.

Table 10
SDM Direct, Indirect, and Total Effects Decomposition

Variable	$\alpha = 1$			$\alpha = 2$		
	Direct	Indirect	Total	Direct	Indirect	Total
FDI	1.633***	-0.039	1.593	2.305***	1.020	3.325
GDP	0.058***	-0.001	0.056	0.071***	0.031	0.102
MHDI	-0.054***	0.001	-0.053	-0.024*	-0.010	-0.034
CC	5.931***	-0.143	5.789	4.925***	2.179	7.104
TOP	-0.032***	0.001	-0.031	-0.021***	-0.009	-0.031
UPOP	0.107***	-0.003	0.104	-0.002 (ns)	-0.001	-0.002
ρ (W_CE)	-0.025 (ns)			0.307 (ns)		
Pseudo R ²	0.941			0.927		
Log-Likelihood	918.02			885.27		
AIC	-1808.05			-1742.53		

Note: *** $p < 0.001$; * $p < 0.05$; ns = not significant. *Source:* Author's Creation

4.5 SDEM Model Results

Table 11
SDEM Model Estimates

Variable	$\alpha=1$ Coeff	St. Err	z-stat	P	$\alpha=2$ Coeff	St. Err	z-stat	p
Constant	304.557	38.329	7.945	0.000	47.668	13.122	3.632	0.000
FDI	1.632	0.116	14.012	0.000	1.644	0.113	14.529	0.000
GDP	0.057	0.006	9.008	0.000	0.059	0.005	10.138	0.000
MHDI	-0.054	0.010	-5.069	0.000	-0.054	0.010	-5.099	0.000
CC	5.933	0.372	15.942	0.000	5.604	0.977	5.735	0.000

TOP	-0.031	0.002	-11.287	0.000	-0.031	0.002	-11.286	0.029
UPOP	0.106	0.024	4.361	0.000	0.101	0.020	4.912	0.000
W_FDI	-100.397	8.714	-11.520	0.000	-23.685	2.679	-8.838	0.000
W_GDP	0.678	0.169	4.013	0.000	0.172	0.109	1.579	0.114
W_MHDI	1.400	0.175	7.960	0.000	-0.398	0.090	-4.405	0.000
W_CC	-64.031	11.384	-5.624	0.000	-7.615	5.603	-1.359	0.174
W_TOP	1.022	0.083	12.244	0.000	0.162	0.049	3.273	0.001
W_UPOP	2.624	0.305	8.602	0.000	0.795	0.123	6.411	0.000
λ (Lambda)	0.229	0.494	0.463	0.642	0.236	0.508	0.464	0.642
Pseudo R ²	0.941				0.941			
Log-Likelihood	919.292				918.097			
AIC	-1812.585				-1810.195			
SIC	-1765.333				-1762.943			

Note: All variables are at natural log, Dependent variable: CE. Source: Author's Creation

The SDEM yields Pseudo R² = 0.941 and AIC = -1812.59 for $\alpha = 1$ (the single-best model fit in our study). Relative to SDM estimates, all direct effects are significant ($p < 0.001$) and highly stable: FDI (1.633), CC (5.934), UPOP (0.106), MHDI (-0.054) and TOP (-0.032). Likewise, Zhang et al. (2023) observed that local direct effects consistently exceed indirect effects in their sample of RCEP member states. Most importantly, the spatial error parameter $\lambda = 0.229$ ($p < 0.643$) is not statistically significant; suggesting that once spatially lagged covariates are controlled, residual spatial autocorrelation is fully absorbed.

This provides evidence to the fact that the spatial error correlation identified in the SEM was primarily due to the omitted spatially structured covariates, which are now captured by the WX terms, rather than to independent unobserved spatial shocks. As Elhorst (2014) has cogently argued, an insignificant λ in the SDEM suggests that the SDEM is, in effect, reduced to the SDM, which consequently represents the preferred policy-relevant specification.

4.6 Consolidated Model Comparison

Table 12 presents a consolidated comparison of models across all four spatial specifications, facilitating principled model selection.

Table 12
Model Fit Comparison Across All Spatial Specifications

Model	A	Pseudo R ²	Log-Likelihood	AIC	SIC	Std. Error	Spatial Parameter
SAR	1	0.899	842.39	-1668.78	-1639.70	0.0119	$\rho = -0.336^\dagger$
SAR	2	0.898	841.65	-1667.30	-1638.22	0.0120	$\rho = 0.114$ (ns)
SEM	1	0.898	843.56	-1673.11	-1647.67	0.0119	$\lambda = -0.997^*$
SEM	2	0.898	842.55	-1671.10	-1645.66	0.0119	$\lambda = -0.915^{**}$
SDM	1	0.941	918.02	-1808.05	-1757.16	0.0091	$\rho = -0.025$ (ns)
SDM	2	0.927	885.27	-1742.53	-1691.65	0.0102	$\rho = 0.307$ (ns)
SDEM	1	0.941	919.29	-1812.59	-1765.33	0.0091	$\lambda = 0.229$ (ns) ← BEST FIT
SDEM	2	0.941	918.10	-1810.20	-1762.94	0.0091	$\lambda = 0.236$ (ns)

Note: Preferred model: SDEM $\alpha=1$ (lowest AIC; higher Pseudo R²; insignificant $\lambda \rightarrow$ reduces to SDM). SDM ($\alpha=1$) is recommended for spillover policy analysis. ** $p < 0.01$; * $p < 0.05$; † $p < 0.10$; ns = not significant. Source: Author's Creation

The SDEM ($\alpha = 1$) has the lowest AIC (-1812.59) and highest log-likelihood (919.29) values for consideration to be the statistically preferred specification. The SDM ($\alpha = 1$) is empirically equivalent, given the insignificance of the SDEM's λ , and assumed to be the preferred specification for policy interpretation being offering a cleaner decomposition of direct and indirect effects (LeSage & Pace, 2009). The SAR and SEM have similar goodness-of-fit (Pseudo $R^2 \approx 0.898$), but are outperformed by the SDM/SDEM family on all criteria, confirming that spatially lagged covariates are important when modelling carbon emissions in SAARC. This result is directly analogous to that of Zhang et al. (2023) for RCEP countries, where the SDM outperformed simpler spatial specifications.

5. Discussion

5.1 FDI and the Pollution Haven Hypothesis

Inward FDI, with direct elasticities ranging from 1.63 to 2.31, appeared to be the largest and most robustly significant driver of carbon emissions across all the four spatial models and both distance-band specifications in the SAARC economies. Like most prior spatial studies that holds empirically for South Asian region, this provides strong support for the PHH (Xing and Kolstad, 2002). Furthermore, the finding is robustly supported by the earlier works of Nur Mozahid et al. (2022), Akram et al. (2025) and Sadiq et al. (2026) in the SAARC context.

In addition, regional FDI inflows tend to be energy-intensive and concentrated in the manufacturing and infrastructure sectors, creating a scale effect that outweighs technology transfer and technique effects. Consistent with the findings of Lin et al. (2022) that PHH and PHE co-exist, the SDM's negative FDI indirect effect (-0.039, $\alpha = 1$) suggests that FDI increases domestic emissions while marginally reducing those of neighbours through competitive displacement. Also, Satoglu and Salmon (2025) provide an important institutional nuance that environmental policy stringency moderates the FDI-emissions relationship.

5.2 Governance Intensity, Urbanisation, and GDP

The control of corruption (CC) consistently yields the largest absolute direct effect in the SDM (5.931, $\alpha = 1$), confirming that government effectiveness, reliance on environmental regulation, and the application of policy implementation for a safe and sound environment for foreign investors are the dominant structural determinants of emissions. This finding aligns with Galinato and Galinato (2012), and the control of corruption nexus documented for Pakistan by Mahmood et al. (2021). In contrast, Wang et al. (2018) concluded that control of

corruption adversely affects the carbon emissions in BRICS economies. Likewise, Padhan and Bhat (2025) provide direct SAARC-level confirmation that institutional quality is negatively associated with CO₂ emissions. Urban population growth (UPOP) exerts a direct effect under $\alpha = 1$ (0.107), consistent with Seto et al. (2014) and Azam et al. (2022), but result becomes statistically insignificant under $\alpha = 2$. This confirms that urbanisation's emissions footprint is highly localised rather than regionally diffused. Also, GDP per capita retains a small but consistent positive effect across all models, reinforcing the finding that SAARC economies remain on the EKC's ascending slope, as documented by Dua et al. (2024) and Wang et al. (2024).

5.3 Human Development and Trade Openness

Human development (MHDI) switches sign across model families, positive in SAR and SEM (consistent with the early-development consumption effect) but negative in the SDM (-0.054, $p < 0.001$). This sign reversal is theoretically coherent in the light of Wang et al.'s (2024) heterogeneous EKC findings; once spatially lagged covariates absorb regional covariation, the net effect of human capital is emissions-reducing, caused by rising environmental awareness and service-sector reorientation. Trade openness (TOP) retains a small but consistently negative emissions effect, supportive of the technique effect hypothesis (Grossman & Krueger, 1995), though Mehmood (2024) cautions that composition effects may temporarily elevate emissions in SAARC's specialised export sectors.

5.4 Spatial Dependence and Regional Policy Implications

The significant negative Moran's I (-0.045 to -0.053) and SAR spatial lag ($\rho = -0.336$, $\alpha = 1$) provide evidence of a pattern consistent with the institutional heterogeneity of SAARC. The significant SEM λ (-0.997 to -0.915) suggests that unobserved, cross-border shared regional shocks, such as monsoon-led commonality of energy-demand seasonality, synchronised domestic infrastructure investment announcements or spatially correlated development aid flows, exhibit negative autocorrelation. In other words, coordinated positive environmental shocks (induced through a SAARC-wide renewable energy installation programme or carbon tax or pricing policy) may bring about more than proportionate regional emission reductions. This, compared to the linear aggregation of country-specific effects, provides a strong economic rationale for a SAARC-wide climate change coordination platform, similar to regional environmental agreements in other trading blocs.

6. Conclusion and Policy Implications

The present study offers the most detailed spatial econometric analysis of the drivers of carbon emissions across SAARC countries (1990-2024), using four spatial model specifications (SAR, SEM, SDM, and SDEM), each with two distance-decay parameters. The first conclusion drawn from the study comprises inadequacy of OLS for the SAARC carbon emissions data. Significant spatial lag dependence (confirmed by LM diagnostics) mandates spatial modelling for unbiased inference. Second, FDI remains the dominant positive driver, across all the four models, robustly supporting the PHH. By considering its spatial spillover effect being negative (under $\alpha = 1$), we confirm the PHH-PHE spatial co-existence for SAARC. Third, the SDM and SDEM substantially outperform SAR and SEM, revealing the empirical importance of covariate spillovers (especially for FDI and industrial carbon intensity) that otherwise missed by the simpler spatial specifications. Finally, the SDEM's insignificant λ indicates that SEM's spatial error correlation arises from omitted spatially structured covariates (not independent spatial shocks), making it the preferred policy-analysis specification.

As a result, major policy recommendations, aligning with green transition priorities, include: i) SAARC-level green FDI governance frameworks requiring environmental impact assessments for carbon-intensive investments; ii) bilateral investment treaty clauses that incentivise low-carbon project design; iii) the quality of governance standards targeting the dominant control of corruption (CC) driver; iv) sustainable urban planning mandates for rapidly growing South Asian cities; and v) coordinated regional renewable energy deployment strategies that exploit the amplifying regional spillover effect as identified in the SEM spatial error structure. As the annual emission lags are not exploited in the current static panel framework, using a dynamic SDM could have allowed us to capture temporal spillovers in future research. Also, the inclusion of sectoral disaggregation of FDI to account for both green and brown capital flows would have allowed for a more nuanced test of PHH against PHE within a spatial framework.

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Declarations

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Authors' Contributions

Both authors contributed substantively to all stages of this research. **Bharat Singh:** conceptualisation, data curation, formal analysis, econometric modelling (SAR, SEM, SDM, and SDEM), spatial weight matrix construction, diagnostic testing, visualisation, original draft preparation, and corresponding author responsibilities. **Rakshit Negi:** conceptualisation, research design, supervision, critical review and editing of all manuscript sections, validation of empirical results, and policy interpretation. All authors have read, reviewed, and approved the final version of the manuscript prior to submission.

Ethical Approval

This is not applicable. The present study is an empirical macroeconomic and spatial econometric analysis based exclusively on publicly available, anonymised, and aggregate secondary panel data obtained from international repositories (World Bank WDI, UNFCCC, and IEA). The study does not involve human participants, human-derived biological material, animal subjects, or any form of primary data collection that would necessitate ethical approval from an institutional review board or ethics committee.

Consent to Participate

This is not applicable. The study relies entirely on publicly available aggregate national-level data. No individuals, human subjects, or animal participants were recruited, surveyed, interviewed, or otherwise involved in the data collection process. Accordingly, individual informed consent to participate was not required.

Consent to Publish

This is not applicable. The study does not contain any individual-level, personally identifiable, or case-specific data pertaining to human subjects or animals. All data employed

are aggregated, publicly available national statistics. No individual consent to publish is therefore required.

Competing Interests

The authors declare no competing interests with respect to the research, authorship, and/or publication of this article. There are no financial, personal, professional, or institutional relationships that could have influenced the design, conduct, interpretation, or reporting of this study.

Data Availability Statement

The data that support the findings of this study are derived from publicly accessible secondary sources. Carbon dioxide (CO₂) emissions per capita data were obtained from the National Inventory Reports of the United Nations Framework Convention on Climate Change (UNFCCC, 2024; <https://unfccc.int>) and the World Bank's World Development Indicators (WDI, 2025; <https://databank.worldbank.org/source/world-development-indicators>). Additional energy and emissions data were sourced from the International Energy Agency (IEA, 2026; <https://www.iea.org/data-and-statistics>). All other macroeconomic and institutional variables (GDP per capita, trade openness, urban population share, control of corruption, and human development indicators) were retrieved from the World Bank WDI and the United Nations Development Programme (UNDP) databases. The processed panel dataset used in the empirical analysis is available from the corresponding author upon reasonable request.