Spatial Determinants of CO_2 Concentration on Java Island: STIRPAT Framework and SAR Model

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Abstract: Java Island, Indonesia's economic and population hub, faces intense environmental pressure from CO_2 concentration, exhibiting strong spatial dependence across its 118 regencies and cities. This study examines the determinants of CO_2 concentration and their spillover effects using an extended STIRPAT framework and a Spatial Autoregressive (SAR) model, applied to 2024 secondary data from BPS-Statistics Indonesia and Google Earth Engine (GEE). The SAR model outperforms OLS, with lower AIC (364.8979 vs. 489.0563) and BIC (387.0634 vs. 508.4551), confirming spatial effects. In SAR models, interpretation relies on decomposing estimated coefficients into direct effects (impacts within a region) and indirect or spillover effects (impacts transmitted to neighboring regions), allowing a more nuanced understanding of spatial influence. Population density and manufacturing sector GRDP increase emissions, while NDVI and HDI reduce them. Population density and manufacturing sector GRDP increase concentration, while NDVI and HDI reduce them. Notably, indirect (spillover) effects consistently surpass direct effects, driven by commuter flows in urban hubs like Jabodetabek and industrial pollution spillovers. These findings inform regional climate strategies, emphasizing cross-regency reforestation and emission controls to support Indonesia's Enhanced Nationally Determined Contribution (ENDC) goals.
Keyword: Carbon Concentration, Java Island, Spatial Autoregressive Model, Spatial Dependence, STIRPAT Model.

1. Introduction

Carbon dioxide (CO_2) is a dominant greenhouse gas (GHG) driving climate change, primarily emitted through human activities intensified by economic growth and industrialization. These concentration stem largely from the combustion of fossil fuels—such as coal, petroleum, and natural gas—used in energy, transportation, and industrial sectors. In ASEAN countries, CO_2 concentration rose significantly from 1971 to 2019 [1], reflecting heavy reliance on fossil-based energy to meet economic and societal demands. Globally, CO_2 accounts for approximately 76% of GHG concentration when weighted by global warming potential, though this varies by region and sector [2]. By amplifying the greenhouse effect, CO_2 accelerates global warming, leading to severe environmental impacts, including melting polar ice caps, rising sea levels, and more frequent extreme weather events like floods, droughts, and heatwaves, which also threaten biodiversity through habitat degradation and species population declines [2].Samosir et al. noted that mitigating CO_2 concentration is critical to achieving several Sustainable Development Goals (SDGs) [3]. These include SDG 6 (Clean Water and Sanitation), emphasizing access to clean water and sanitation; SDG 11 (Sustainable Cities and Communities), promoting sustainable urban environments; SDG 13 (Climate Action), advocating for climate-resilient technologies; and SDGs 14 and 15 (Life Below Water and Life on Land), focusing on marine and terrestrial ecosystem preservation. In Indonesia, a major contributor to Southeast Asia's concentration, these goals are particularly relevant. The government has committed to reducing GHG concentration by 31.89% independently and up to 43.20% with international support by 2030, relative to a business-as-usual scenario, as outlined in its Enhanced Nationally Determined Contribution (ENDC) [4]. These targets are supported by policies like Presidential Regulation No. 98 of 2021, which establishes a carbon economic value framework, and Government Regulation No. 22 of 2021, which mandates environmental management and GHG emission reductions [5].

With a population exceeding 270 million—the world's fourth largest—Indonesia faces escalating energy demands driven by rapid growth in its industrial, construction, and transportation sectors [6]. However, reliance on fossil fuels, coupled with deforestation and land conversion for agriculture or settlements, significantly contributes to CO_2 concentration. On Java Island, which houses over half of Indonesia's population and serves as an economic hub, CO_2 concentration exhibit spatial interdependence. Economic activities such as commuter flows, logistics networks, and industrial expansion create spillover effects, where CO_2 concentrations in one regency influence air quality in neighboring areas due to pollution diffusion or cross-boundary activities [3, 7]. This spatial dynamic underscores the need for targeted, spatially informed mitigation strategies.

Previous studies have leveraged the STIRPAT (Stochastic Impacts by Regression on Population, Affluence, and Technology) framework with spatial econometric models to analyze CO_2 concentration. For instance, Zhu and Lin (2025) [8] used an extended STIRPAT model to examine livelihood development's impact on CO_2 concentration in China's Yangtze River Delta, highlighting spatial spillovers. Similarly, Lu et al. (2020) [9] applied spatial analysis to identify determinants of carbon concentration in China's construction industry, revealing significant spatial autocorrelation. Liu and Song (2020) [10] employed a spatial Durbin model to assess financial development's effect on CO_2 concentration in China, emphasizing spatial dependencies. Liu and Han (2021) [11] extended STIRPAT to study urbanization and technology impacts on concentration in the Yangtze River Economic Belt, while Weng et al. (2023) [12] used a spatial Durbin model to explore clean energy investment's role in reducing CO_2 concentration. In Indonesia, Samosir et al. (2024) [3] analyzed spatial dependencies in environmental quality, providing a foundation for regional studies. These studies demonstrate the efficacy of combining STIRPAT with spatial econometric approaches, such as the Spatial Autoregressive (SAR) model, in capturing local and spillover effects in densely populated regions like Java.

This study aims to identify the key factors influencing CO_2 concentration in Java's regencies/cities using an extended STIRPAT model with a Spatial Autoregressive (SAR) estimation approach. By analyzing local drivers, it informs targeted mitigation strategies, such as reducing urban pollution and coordinating cross-regency reforestation to lower CO_2 concentrations. These findings contribute to Indonesia's climate mitigation goals and sustainable development strategies.

This study aims to identify the key factors influencing CO_2 concentrations in Java's regencies and cities using an extended STIRPAT model with a Spatial Autoregressive (SAR) estimation approach. By analyzing local drivers (e.g., population density, industrial activity) and assessing spillover effects on neighboring regions, it informs targeted mitigation strategies, such as reducing urban pollution and coordinating cross-regency reforestation to lower CO_2 concentrations. These findings contribute to Indonesia's climate mitigation goals and sustainable development strategies [5,16].

2. Research Method

2.1. Conceptual Framework

This study employs the STIRPAT (Stochastic Impacts by Regression on Population, Affluence, and Technology) model, developed by Dietz and Rosa [13], to analyze the factors influencing CO_2 concentration in regencies and cities across Java Island. The STIRPAT model builds on the IPAT identity (Impact = Population × Affluence × Technology), introduced by Ehrlich and Holdren [14]. The

IPAT identity posits that environmental impact (I) results from the interaction of population (P), affluence (A), and technology (T), expressed as

$$I = P \times A \times T \tag{1}$$

However, the IPAT identity is deterministic, assuming a proportional linear relationship that limits its use in quantitative regression analysis. To address this, the STIRPAT model reformulates IPAT into a stochastic framework suitable for logarithmic regression, with the basic formulation

$$I = a \times P_i^b \times A_i^c \times T_i^d \times e_i \tag{2}$$

where I_i represents environmental impact (e.g., CO_2 concentration, pollution, resource depletion) in region i, P_i, A_i, and T_i denote population, affluence, and technology, respectively, a is a scaling constant, b, c, and d are exponents measuring the elasticity of each factor, and e_i is the error term. For regression analysis, the model is log-transformed as

$$\ln(I_i) = \ln(a) + b\ln(P_i) + c\ln(A_i) + d\ln(T_i) + \ln(e_i). \tag{3}$$

The STIRPAT model is flexible, allowing the inclusion of additional socioeconomic or ecological variables relevant to the study context. In this research, the model is extended to incorporate variables such as population density, economic growth, industrial contribution, vegetation cover (measured by the Normalized Difference Vegetation Index, NDVI), and the number of motor vehicles to capture the determinants of CO_2 concentration in Java. Additionally, the Human Development Index (HDI) is used as a proxy for affluence, as it encompasses education, health, and living standards, reflecting not only consumption levels but also technological capacity and lifestyle patterns in urban and rural regions [8]. The HDI thus captures the quality of life, which influences energy consumption and CO_2 concentration.

Given the spatial interdependence among Java's regencies/cities, driven by factors such as commuter flows and industrial expansion, this study integrates the STIRPAT model with a Spatial Autoregressive (SAR) approach. The SAR model accounts for spillover effects, where CO_2 concentration in one regency/city may influence neighboring regions [3]. This framework combines local factors (population, economy, technology) with spatial dynamics to provide a comprehensive understanding of CO_2 concentration in Java.

2.2. Model Estimation Procedure

This study employs the Spatial Autoregressive (SAR) model to analyze the effects of population, affluence (welfare), and technology—along with other socioeconomic factors—as independent variables on CO_2 concentration (the dependent variable), while accounting for spatial effects across regencies/cities in Java. The SAR model captures spatial autocorrelation in the dependent variable, allowing for spillover effects where concentration in one regency influence neighboring areas. The process for building and estimating the SAR model follows a structured sequence of steps, as outlined below.

Initial Estimation with OLS

Parameters are first estimated using the Ordinary Least Squares (OLS) model, which ignores spatial effects, to establish a baseline

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_k X_k + \varepsilon \tag{4}$$

where:

Y : Dependent variable (CO_2 concentration).

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$X_1, X_2, \ldots, X_k$: Independent variables (e.g., population density, HDI as a proxy for affluence, industrial contribution).
$\beta_0, \beta_1, \ldots, \beta_k$: Estimated parameters.
k : Number of independent variables.
ε : Error term.

Testing for Spatial Autocorrelation
To detect spatial effects, the OLS residuals are tested for spatial autocorrelation using Moran's I statistic. A significant p-value (typically < 0.05) indicates spatial dependence, rendering the OLS model inadequate for unbiased estimation [15]. If spatial autocorrelation is present, a spatial econometric model is required.

Constructing the Spatial Weight Matrix
The spatial weight matrix (W) is constructed using the queen contiguity approach, which defines neighboring regions based on shared borders or vertices. This method is well-suited for irregularly shaped administrative units like regencies/cities in Java and has been effectively applied in prior studies on emission distributions, such as those examining carbon concentration in China's construction industry and SO_2 concentration in Eastern China [9, 16].

Testing for the Spatial Model Selection
To select between the Spatial Autoregressive Model (SAR) and the Spatial Error Model (SEM), Lagrange Multiplier (LM) tests are conducted on the OLS residuals. If the LM-Lag test is statistically significant ($p < 0.05$) while the LM-Error test is not, the SAR model is chosen, indicating spatial dependence in the dependent variable (CO_2 concentration). Conversely, if the LM-Error test is significant while the LM-Lag test is not, the SEM model is selected, indicating autocorrelation in the error term. If both LM-Lag and LM-Error tests are significant, Robust LM tests are performed to determine the dominant model: the model with the higher Robust LM test statistic (SAR or SEM) is preferred. This approach follows established spatial econometrics guidelines [15].

Specification of the SAR Model
Based on the test results, the SAR model is specified as

$$Y_i = \rho \sum_{j=1}^{n} W_{ij} Y_j + \sum_{l=1}^{k} X_{il} \beta_l + \varepsilon_i \tag{5}$$

where:
Y_i : CO_2 concentration in region i.
X_{il} : Independent variables for region i.
β_l : Estimated parameters.
n : Number of observations (regencies/cities).
k : Number of independent variables.
ε_i : Error term.
W_{ij} : Spatial weight matrix element between regions i and j.
ρ : Spatial autoregressive coefficient, measuring spatial dependence.

Model Evaluation
The model's goodness-of-fit is evaluated using the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), which balance explanatory power and model complexity. Lower AIC and BIC values indicate better model performance. The AIC is calculated as

$$\mathrm{AIC} = 2k - 2\ln(L) \tag{6}$$

where k is the number of parameters and L is the maximized likelihood function [17]. The BIC is given by

$$\mathrm{BIC} = k\ln(n) - 2\ln(L) \tag{6}$$

where n is the number of observations [18]. These metrics are standard in spatial econometric studies to ensure model parsimony and robustness [15].

2.3. Data

This study adopts an extended STIRPAT model to analyze the determinants of CO_2 concentration across 118 regencies/cities in Java, Indonesia, for the year 2024. The STIRPAT framework, building on the IPAT identity as core drivers of environmental impact, with flexibility to include additional socioeconomic and ecological variables $[10 - 13]$. Secondary data for 2024 are sourced from the BPS-Statistics Indonesia and google earth engine (GEE), covering all regencies and cities in Java except Kepulauan Seribu Regency, which is excluded because it lacks spatial neighbors due to its location offshore, disconnected from mainland Java, making it unsuitable for the SAR model's contiguity-based spatial weight matrix.

The CO_2 concentration data were derived from the Sentinel-5 Precursor (Sentinel-5P) satellite using datasets available on Google Earth Engine (GEE). This product measures atmospheric carbon monoxide (CO) column number density, which serves as a proxy for near-surface CO_2 concentration. The dataset provides daily global coverage with a spatial resolution of approximately 7 × 7 km, enabling detailed spatial differentiation of air quality and emission patterns. For this study, data were filtered for the period from January 1 to December 31, 2024, and averaged to produce an annual mean concentration map over Java. Mean values were then extracted at the regency/city level using zonal statistics within GEE.

Although CO and CO_2 are chemically distinct gases, CO is commonly used as a proxy for combustion-related CO_2 concentrations due to their shared sources and correlated spatial patterns. Both gases are emitted from fossil fuel combustion, biomass burning, and other anthropogenic activities, making CO a useful indicator of emission intensity, especially in urban and industrial areas. This approach is supported by studies such as [19], which demonstrate that satellite-derived CO concentrations can effectively reflect fossil-fuel CO_2 emission distributions in regional-scale analyses.

Vegetation indicators were assessed using the Normalized Difference Vegetation Index (NDVI), computed from Landsat 8 Collection 2 Level-2 Surface Reflectance data. NDVI was calculated using the red (Band 4) and near-infrared (Band 5) bands with the formula: (NIR − RED) / (NIR + RED). The dataset was filtered for July 2024, representing the dry season in Java, to minimize cloud contamination. Only scenes with less than 10% cloud cover were included. A median composite was generated to reduce noise, and NDVI values were aggregated to the regency/city level using mean zonal statistics. This index reflects vegetation density and health, which indicates the land's potential to absorb carbon and mitigate CO_2 concentrations.

Table 1. Variable definitions.

Description	Measurement	Unit	Source
Total CO_2 Concentration	Total annual CO_2 concentration	g/m^3	GEE
Population density	Total population divided by area	Persons/km²	BPS
Vegetation Index (NDVI)	Normalized index from NIR and red band reflectance	Index (-1 to 1)	GEE
Human Development Index (HDI)	Composite index of life expectancy, education, and living standards	Index (0–100)	BPS

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Manufacturing Sector GRDP	Percentage of GRDP from the manufacturing sector	Percent	BPS
Information and Communication Sector GRDP	Percentage of GRDP from the information and communication sector	Percent	BPS

The variables used in the extended STIRPAT model are detailed in Table 1, including their definitions, measurements, units, and sources. Population density represents the population (P) component, capturing demographic pressure on concentration. The Human Development Index (HDI) serves as a proxy for affluence (A), reflecting quality of life through education, health, and living standards, which influence consumption patterns and energy use [8]. The Gross Regional Domestic Product (GRDP) of the manufacturing sector (as a percentage of total GRDP) is included as an additional economic variable, representing industrial activity's contribution to concentration. The GRDP of the information and communication sector (as a percentage of total GRDP) proxies technological advancement, as this sector often drives innovation and efficiency [11]. The Normalized Difference Vegetation Index (NDVI) is included as an ecological variable, measuring vegetation cover's role in carbon sequestration. The number of motor vehicles captures transportation-related concentration, a significant factor in Java's urbanized regions.

3. Result and Discussion

3.1. Spatial Distribution of CO_2 Concentration

The distribution of CO_2 concentration across 118 regencies and cities in Java, Indonesia, exhibits significant spatial variation, as shown in Figure 1. High concentration are concentrated in urban and industrial hubs, including Greater Jakarta (Jabodetabek), Bandung, and Surabaya, driven by dense populations and industrial activities. Conversely, lower concentration are observed in rural and less industrialized areas, particularly in the southern parts of Banten and West Java provinces and the southern coastal regions of Central and East Java. The thematic map uses color gradation to represent emission levels, with darker shades indicating higher concentration and lighter shades denoting lower concentration. The map also reveals clustering patterns, where high-emission regions are often adjacent to other high-emission areas, suggesting potential spillover effects consistent with spatial dependence.

3.2. OLS Regression Results

To provide a baseline, multiple linear regression (MLR) was conducted using the ordinary least squares (OLS) method, ignoring spatial dependence. The results, presented in Table 2, estimate the effects of population density, NDVI, HDI, Manufacturing Sector GRDP, and Information and Communication Sector GRDP on CO_2 concentration.

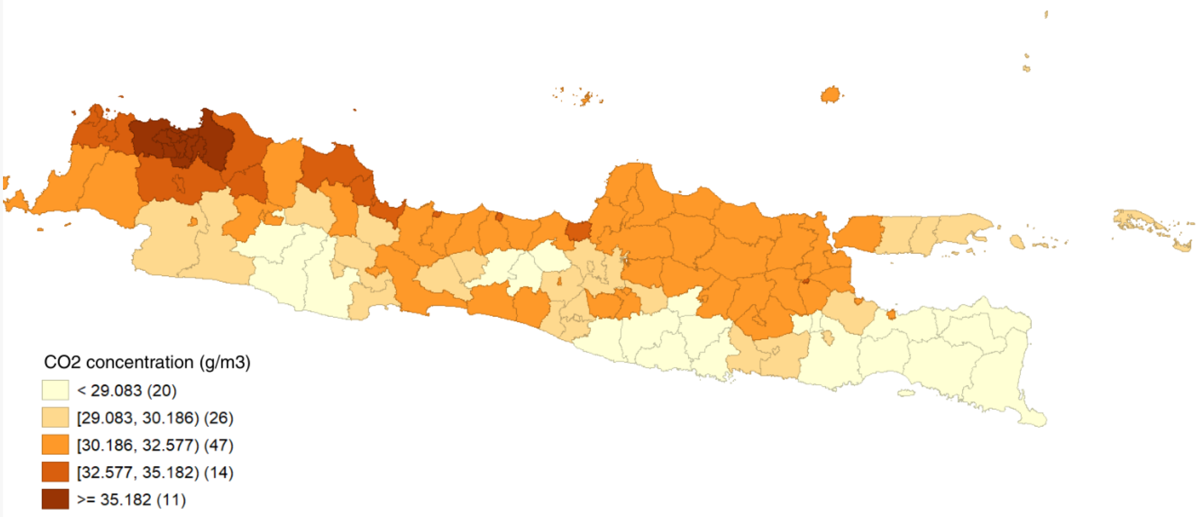

Figure 1. Map of CO_2 Emission Distribution.

The OLS results indicate that, at a 5% significance level, the natural logarithm of population density, NDVI, and HDI significantly influence CO_2 concentrations, serving as a baseline for comparison with the Spatial Autoregressive (SAR) model. Higher population density is associated with increased concentrations, reflecting urban activity, while NDVI (-12.0833) suggests vegetation reduces concentrations via carbon sequestration [8]. The unexpected negative HDI coefficient (-0.1455) may indicate efficiency or green policies in high-HDI regions, warranting further investigation. However, OLS is invalid due to spatial autocorrelation, and the SAR model, which captures spillover effects, provides reliable estimates (subsection 3.5). Manufacturing and Information Sector GRDP show no significant effects (p-values > 0.05).

Table 2. Estimated coefficients of the OLS model.

Variable	Coefficient	Std. Error	p-value
Intercept	32.7461	4.2159	0.0000
Population density (ln)	1.6043	0.3162	0.0000
NDVI	-12.0833	4.3158	0.0060
HDI	-0.1455	0.0608	0.0183
Manufacturing sector GRDP	0.0187	0.0123	0.1301
Information and communication sector GRDP	-0.0511	0.0793	0.5207

Classical assumption tests were conducted to ensure the OLS model satisfies the Best Linear Unbiased Estimator (BLUE) criteria, with results presented in Table 3.

Table 3. Results of classical assumption tests for OLS.

Assumption test	Test statistic	p-value

Jarque-Bera test	0.7014	0.7042
Breusch-Pagan test	17.744	0.0033
Durbin-Watson test	0.9782	0.0000
Independent variable		VIF
Population density (ln)		3.8257
NDVI		2.6117
HDI		3.5508
Manufacturing sector GRDP		1.5353
Information and communication sector GRDP		2.2784

The OLS model meets the normality assumption (Jarque-Bera p-value = 0.7042 > 0.05) and the no-multicollinearity assumption, as all Variance Inflation Factor (VIF) values are below 5, indicating no severe collinearity among independent variables. However, the model violates two assumptions: the Breusch-Pagan test (p-value = 0.0033 < 0.05) confirms heteroskedasticity, indicating non-constant residual variance, and the Durbin-Watson test (p-value = 0.0000) indicates positive autocorrelation. These violations suggest that OLS estimates may be inefficient or biased, necessitating a spatial regression approach to account for spatial dependence.

3.3. Spatial Dependence Analysis

To construct the spatial weight matrix for the SAR model, the number of neighbors for each regency/city was determined using the queen contiguity method, as shown in Figure 2. On average, each region has three to four neighbors, but significant variation exists. For example, Bogor Regency, centrally located with broad geographic coverage, has up to 11 neighbors, while some municipalities have only one. This diversity in spatial connectivity underscores the need for spatial modeling.

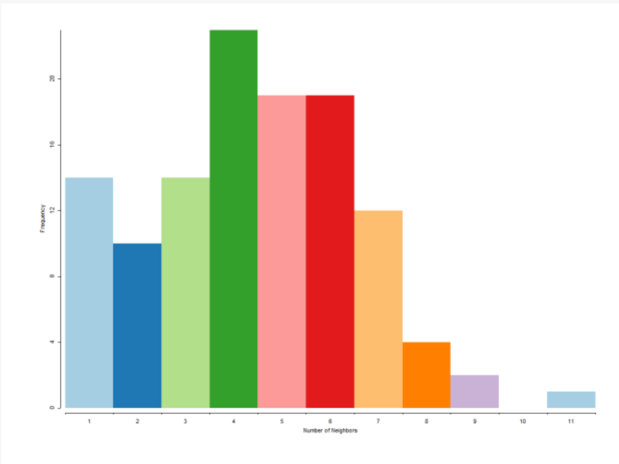

Figure 2. Number of neighbors based on queen contiguity weights.

A randomization test of Moran's I was conducted to assess spatial dependence in CO_2 concentration, with results shown in Figure 3. Using queen contiguity weights, the Moran's I value is 0.7754, with a z-score of 12.0365 and a pseudo p-value of 0.0010, indicating strong positive spatial autocorrelation. This means that regions with high CO_2 concentration tend to be surrounded by other high-emission regions, and low-emission regions are adjacent to similar areas, confirming the clustering observed in Figure 1. The observed Moran's I (green line) lies far from the reference distribution of 999 permutations, with no permuted values exceeding the observed statistic, providing robust evidence of spatial dependence.

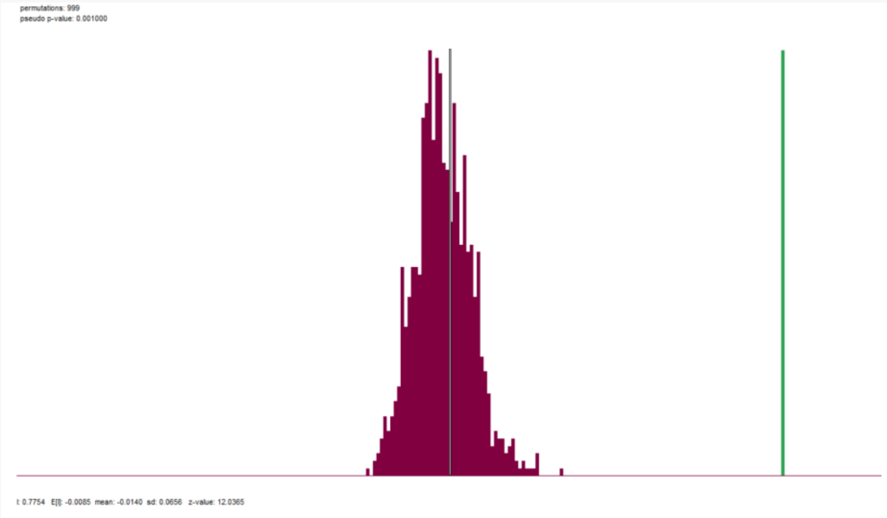

Figure 3. Moran's I of CO_2 concentration with 999 permutations.

Given the presence of spatial autocorrelation, diagnostic Lagrange Multiplier (LM) tests were conducted to select the appropriate spatial model, with results presented in Table 4. Both LM lag and LM error tests are significant at the 5% level ($p < 0.05$), indicating spatial dependence. However, the Robust LM lag test remains significant ($p = 0.0000$), while the Robust LM error test is not ($p = 0.8725$), suggesting that the Spatial Autoregressive (SAR) model, which accounts for spatial dependence in the dependent variable (CO_2 concentration), is the most appropriate specification [15].

Diagnostic tests confirmed both heteroskedasticity (Breusch-Pagan test, $p < 0.05$) and spatial autocorrelation (Moran's I, $p < 0.05$) in the data. While Geographically Weighted Regression (GWR) can address heteroskedasticity by modeling spatially varying coefficients, the LM test indicated that the SAR model was the most appropriate (robust LM-lag: $p < 0.01$; robust LM-error: $p > 0.05$). SAR was chosen because it explicitly captures spillover effects of CO_2 concentrations across neighboring regencies, aligning with the study's focus on spatial interdependence and regional mitigation strategies.

Table 4. Diagnostic LM tests for spatial dependence.

Diagnostic Test	Test statistic	p-value
LM lag	102.2504	0.0000
LM error	72.3642	0.0000
Robust LM lag	29.9120	0.0000
Robust LM error	0.0257	0.8725
SARMA	102.2762	0.0000

3.4. SAR Model Results

The SAR model was estimated to address the spatial dependence and OLS assumption violations, incorporating the spatial lag of CO_2 concentration. The results, presented in Table 5, show the estimated coefficients, standard errors, and p-values for the variables and the spatial autoregressive coefficient (ρ). The significant ρ (0.0765, $p = 0.0000$) confirms spatial spillover effects, where concentration in one region are influenced by neighboring regions, highlighting the interconnected nature of environmental impacts in Java's densely populated and economically integrated landscape.

The SAR model reveals that population density, NDVI, HDI, and manufacturing sector GRDP significantly influence CO_2 concentration at the 5% level, while information and communication sector GRDP remains insignificant. Compared to OLS (Table 2), the SAR model adjusts for spatial bias, reducing the magnitude of coefficients (e.g., ln(population density) from 1.6043 to 0.5990), suggesting that OLS overestimated effects due to unaccounted spillovers. The positive coefficient for population density (0.5990) indicates that a 1% increase in population density raises concentration by 0.599%, driven by urban expansion and energy demand in Java's megacities like Jakarta, where commuter flows amplify regional pollution [16]. However, the negative HDI coefficient (-0.0725) challenges the traditional STIRPAT view of affluence increasing concentration; in Java, higher HDI may promote sustainable behaviors, such as public transport use or renewable energy adoption, offsetting consumption-driven concentration [8].

Table 5. Estimated coefficients of the SAR model.

Coefficient	Estimate	Std. Error	p-value
Intercept	9.4469	2.6326	0.0003
Population density (ln)	0.5990	0.1780	0.0008
NDVI	-6.7589	2.2628	0.0028
HDI	-0.0725	0.0324	0.0250
Manufacturing sector GRDP	0.0148	0.0064	0.0205
Information and communication sector GRDP	0.0448	0.0413	0.2782
ρ	0.0765	0.0437	0.0000

NDVI's negative coefficient (-6.7589) underscores vegetation's role in sequestration, particularly in Java's rural southern coasts, where forest cover mitigates urban spillover [10]. The positive manufacturing sector GRDP coefficient (0.0148) highlights industrialization's environmental cost, as factories in hubs like Surabaya release pollutants that spread regionally, exacerbating climate vulnerability in adjacent agricultural areas [9]. The insignificant information and communication sector GRDP (0.0448) suggests that technological advancements in this sector have not yet translated into emission reductions, possibly due to limited digital infrastructure in rural Java, where technological advancements are less widespread [11].

Table 6. Direct, indirect, and total effects of the SAR model on CO_2 concentration.

Coefficient	Direct Effect	p-value	Indirect Effect	p-value	Total Effect	p-value
Population density (ln)	0.7543	0.0003	1.7953	0.0020	2.5496	0.0007
NDVI	-8.5119	0.0031	-20.2587	0.0130	-28.7707	0.0071
HDI	-0.0913	0.0230	-0.2174	0.0412	-0.3087	0.0313
Manufacturing sector GRDP	0.0186	0.0170	0.0443	0.0496	0.0630	0.0345
Information and communication sector GRDP	0.0564	0.2808	0.1343	0.3135	0.1907	0.3003

Table 6 decomposes direct, indirect, and total effects, revealing that indirect effects dominate for all significant variables, underscoring Java's economic and environmental interconnectivity. The larger indirect effects imply that local policies must consider regional dynamics; for example, population growth in Jakarta spills over to Bogor, amplifying concentration through commuter traffic [11]. NDVI's strong spillover (-20.2587 indirect) suggests reforestation in one regency (e.g., Banten's southern forests) benefits neighbors via air quality improvements, supporting integrated green corridors across Java to maximize carbon sequestration [10]. HDI's negative spillover (-0.2174) indicates that human capital improvements in affluent areas like Surabaya diffuse sustainable practices regionally, but uneven development in rural Java limits this [8]. Manufacturing's positive spillover (0.0443) highlights pollution from industrial clusters like Bandung affecting adjacent agriculture, calling for emission caps with cross-regency enforcement [9]. These findings align with studies in Indonesia and similar urbanized regions, where population and industrial activities amplify concentration through spatial spillovers, while vegetation and human development mitigate them [11, 12, 20]. For instance, Liu & Han (2021) found that urbanization-driven concentration in China's Yangtze River Economic Belt have significant spillover effects due to transportation networks, analogous to Jabodetabek's commuter dynamics [11]. Similarly, Weng et al. (2023) reported non-linear urbanization effects in Indonesia, with spillovers dominating in densely populated regions [12].

These results have critical policy implications. The dominance of indirect effects suggests that local climate policies in Java must be coordinated regionally. For example, reducing concentration in Jakarta requires managing commuter flows to Bogor and Tangerang through integrated public transport systems, such as expanding TransJakarta or commuter rail networks [11]. Reforestation programs in rural areas, like southern Central Java, should be scaled up to create green belts that benefit neighboring urban centers, aligning with Indonesia's Enhanced Nationally Determined Contribution (ENDC) goals [4]. Industrial emission caps in hubs like Bandung and Surabaya must involve cross-regency enforcement to mitigate spillover to agricultural zones, protecting food security [9]. The negative HDI effect highlights the need to promote sustainable practices in high-HDI regions, such as green technology adoption, while addressing rural-urban disparities to extend these benefits [8]. Ignoring spillovers risks underestimating impacts, as seen in similar STIRPAT studies in Indonesia [12, 20].

3.5. Model Evaluation

Model performance was compared using the AIC and BIC, with results in Table 7. The SAR model's lower AIC (364.8979 vs. 489.0563) and BIC (387.0634 vs. 508.4551) confirm its superior fit, capturing spatial effects and reducing estimation bias [15].

Table 7. Model evaluation.

Evaluation metric	OLS	SAR
AIC	489.0563	364.8979
BIC	508.4551	387.0634

4. Conclusion

Moran's I test confirms strong positive spatial autocorrelation in CO_2 concentration, indicating regional interdependence across Java's 118 regencies and cities. The SAR model, validated by LM tests, outperforms OLS and SEM, revealing that population density and manufacturing sector GRDP increase concentration, while NDVI and HDI reduce them. Critically, indirect (spillover) effects exceed direct effects for all significant variables, driven by Java's integrated urban-rural economy. This underscores the need for coordinated policies, such as regional reforestation to leverage NDVI spillovers, cross-regency industrial emission controls, and urban planning to manage population density impacts. These align with Indonesia's climate goals under the Enhanced Nationally Determined Contribution (ENDC). For instance, expanding green corridors in rural Java and enhancing public transport in Jabodetabek can mitigate spillovers from urban centers. Future research could incorporate dynamic spatial panels to explore temporal spillovers and refine policy strategies.

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