Ebrahim, Ehab Ebrahim Mohamed; Abonazel, Mohamed R.; Shalaby, Ohood A. et al.

Periodical Part

Studying the impact of socioeconomic and environmental factors on nitrogen oxide emissions : spatial econometric modeling

International Journal of Energy Economics and Policy

Reference: In: International Journal of Energy Economics and Policy Studying the impact of socioeconomic and environmental factors on nitrogen oxide emissions : spatial econometric modeling 15 (2025).
https://www.econjournals.com/index.php/ijeep/article/download/18300/8600/42284.
doi:10.32479/ijeep.18300.

International Journal of Energy Economics and Policy

ISSN: 2146-4553

available at http: www.econjournals.com

International Journal of Energy Economics and Policy, 2025, 15(2), 248-259.

Studying the Impact of Socioeconomic and Environmental Factors on Nitrogen Oxide Emissions: Spatial Econometric Modeling

Ehab Ebrahim Mohamed Ebrahim[1,2], Mohamed R. Abonazel[3]*, Ohood A. Shalaby[4], Walaa Abdullah Abdullah Albeltagy[5]

[1]Department of Economics, Faculty of Commerce, Kafrelsheikh University, Kafrelsheikh, Egypt, [2]Department of Economics, College of Business, Imam Mohammad Ibn Saud Islamic University (IMSIU), Riyadh, Saudi Arabia, [3]Department of Applied Statistics and Econometrics, Faculty of Graduate Studies for Statistical Research, Cairo University, Giza, Egypt, [4]National Center for Social and Criminological Research, Giza, Egypt, [5]Department of Economics, Faculty of Commerce, Mansoura University, Mansoura, Egypt. *Email: mabonazel@cu.edu.eg

Received: 16 October 2024 **Accepted:** 24 January 2025 **DOI:** https://doi.org/10.32479/ijeep.18300

ABSTRACT

This study aims to identify the socioeconomic drivers of nitrogen oxide (NOx) emissions and their spatial relationships in 31 Chinese regions in 2022 using spatial econometric models. Our research incorporates a comprehensive set of variables, including electricity consumption, per capita household consumption expenditure (PCEXP), Expenditure on research and development (R&D), numbers of vehicle in operation, population density, green-covered areas, land use patterns, and cultivated land area. Following a comparative analysis, we selected the spatial Durbin model (SDM) as the most appropriate statistical model for analyzing provincial NOx emissions. Results indicate that electricity consumption and land use patterns are significant contributors to NOx emissions. Specifically, we found that a one billion kilowatt-hour (kWh) increase in electricity consumption corresponds to an increase of approximately 367.3 tons of NOx emissions within the same region. Similarly; a one-million-hectare expansion in land used for urban, rural, industrial, and mining activities is associated with an increase of about 161.9 thousand tons of NOx emissions in the same region. Importantly, our analysis revealed positive spillover effects for PCEXP and cultivated land area, suggesting that changes in these factors in one region can influence NOx emissions in neighboring regions. Contrary to some previous findings and prevailing assumptions, urban population density and green-covered areas did not show significant direct or indirect impacts on NOx emissions. This unexpected result challenges existing notions about urbanization and green space effects on air quality, warranting further investigation. Based on these findings, the study proposes recommendations for mitigating NOx emissions and improving air quality in Chinese regions.

Keywords: Air Pollution; NOx Emissions; Economic Development; Energy Consumption; China; Spatial Dependence
JEL Classifications: C10, C21, Q50, Q53, Q56

1. INTRODUCTION

As China continues to navigate its role as a global economic powerhouse, it faces the critical task of addressing the accompanying environmental issues to ensure long-term, sustainable development, Abdelwahab et al. (2024). The gravity of this challenge is underscored by recent data from the Community Emissions Data System (CEDS) 2024 processed by Our World in Data, which highlights China's persistent status as the world's leading emitter of air pollutants over the study period from 2017 to 2022. Particularly concerning are the nation's NOx emissions, which reached a staggering 19.6 million tons in 2022 and 23.49 million tons in 2017, accounting for 17.3% and 19.0% of global NOx emissions respectively.

However, according to the 2022 China Ecological Environment Status Bulletin, published by the Ministry of Ecology and Environment, a majority of China's urban centers have made significant strides in air quality improvement. The report indicates that 213 out of 339 cities —representing 62.8% of the total—successfully met the established ambient air quality standards. While, the remaining 126 cities, accounting for 37.2%, still grappled with air quality levels exceeding the stipulated standards, Yan et al. (2024). IHME, Global Burden of Disease (2024) - with minor processing by Our World in Data – highlighted that more than 2.35 million people died in China because of air pollution in 2021. On a global scale, The World Health Organization (WHO) estimates that approximately 4.2 million premature deaths occur each year as a result of exposure to outdoor air pollution, with the majority of these fatalities occurring in low- and middle-income countries, according to Wu and Liu (2023).

While this data reflects notable progress in China's battle against air pollution, it also underscores the persistent challenges that require immediate and focused action. The substantial number of cities still failing to meet air quality benchmarks highlights the ongoing need for robust environmental policies and concerted efforts to address the complexities of urban air pollution across the nation.

Understanding the main determinants of NOx emissions is crucial for developing effective strategies to mitigate their impact. This literature review investigates the relationship between NOx emissions and two key factors of interest in our study: economic development and built environment characteristics.

The relationship between economic development and pollution emissions has been extensively explored in academic literature, with many studies grounded in the Environmental Kuznets Curve (EKC) hypothesis, first proposed by Grossman and Krueger (1991). This hypothesis posits an inverted U-shaped relationship between economic growth and environmental degradation. Initially, as economies develop, pollutant emissions increase and air quality deteriorates. However, upon reaching a critical point in economic development, further growth leads to a reduction in pollution and an improvement in environmental conditions, Zhou et al. (2018), Zhang et al. (2019a), and Han et al. (2021).

Numerous studies have been devoted to investigating and validating the EKC hypothesis, including the works of Kharbach and Chfadi (2017) and Gill et al. (2018). However, the existence of the EKC remains a subject of debate within the scientific community. Research findings vary significantly depending on the geographical focus, pollutants examined, and methodologies employed. Consequently, a definitive consensus on the EKC hypothesis has yet to be established, highlighting the complex and nuanced nature of the relationship between economic growth and environmental impact.

In the following, we review the relationship between some economic development indicators and NOx emissions highlighting the complex interplay of these factors.

Industrial Structure and Energy Consumption: The composition of a country's industrial sector and its energy consumption patterns significantly influence NOx emissions. For example, Heavy industries, particularly in the manufacturing and energy sectors, are major contributors to NOx emissions, Xiang et al. (2024) and Van Vuuren et al. (2011). On the other hand, several studies demonstrated that the transition from coal to cleaner energy sources has been shown to reduce pollution emissions, for example, the studies conducted by Song et al. (2021) and He et al. (2023) find that redirecting and advancing technological progress accompanied economic development contribute to carbon-free transition solutions.

Urbanization and Economic Transitions: Rapid urbanization, often accompanying economic development, has complex effects on NOx emissions. Urban areas typically have higher concentrations of NOx due to increased traffic, human daily life, and industrial activities, Diao et al. (2018). However, urbanization can also lead to more efficient resource use and potentially lower per capita emissions. In this context, Poumanyvong and Kaneko (2010) conducted an empirical study examining the impact of urbanization on energy consumption and CO_2 emissions across different stages of economic development. Their research employed the Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model, analyzing a balanced panel dataset comprising 99 countries over 30 years from 1975 to 2005. Contrary to conventional assumptions, the research revealed that urbanization's effect on energy consumption and emissions is not uniform across different stages of economic development. In low-income regions, urbanization correlates with decreased energy use. Conversely, in middle- and high-income areas, urbanization is associated with increased energy consumption. This nuanced understanding challenges one-size-fits-all approaches to urban environmental policies. Furthermore, the study highlights a significant trend in developing countries: the transition from manufacturing-based to service-based economies. This shift may have notable positive implications for NOx emissions patterns, as service industries generally have lower emission intensities compared to heavy manufacturing.

Trade and Foreign Direct Investment (FDI) play significant roles in shaping global NOx emissions patterns, primarily through the mechanism described by the pollution haven hypothesis. This theory, as elaborated by Levinson and Taylor (2008), suggests that multinational corporations from industrialized nations often seek to establish operations in countries offering the most cost-effective combination of resources, labor, and regulatory environments. The pollution haven hypothesis posits that companies tend to relocate their polluting industries to nations with less stringent environmental regulations, typically developing countries eager for economic growth. This relocation occurs because stricter environmental standards in developed nations increase operational costs, making countries with lax regulations more attractive for investment. Consequently, this can lead to a concentration of polluting industries in areas with weak environmental enforcement, potentially exacerbating local and global environmental degradation. However, the relationship between FDI and environmental impact is not uniformly negative.

While there are concerns that the environmental costs of increased emissions might offset the economic benefits of FDI, an alternative perspective exists. FDI can potentially contribute to environmental improvement if it brings with it green technologies and sustainable practices. These advanced technologies and methods can create positive spillover effects, encouraging domestic industries to adopt cleaner production processes, Demena and Afesorgbor (2020).

The dual nature of FDI's environmental impact underscores the complexity of the issue. It highlights the need for careful policy consideration to balance the economic benefits of foreign investment with environmental protection. Effective strategies might include incentivizing green FDI, promoting technology transfer, and fostering international cooperation to standardize environmental regulations, thereby mitigating the negative effects of the pollution haven phenomenon while maximizing the potential for positive environmental outcomes and faster economic growth, Mauro (2024). Accordingly, countries which involve renewable energy development and enhancing green industrial strategies that boost productivity, have a competitive advantage in the global markets through international trade, and attract more FDI Cardinale *et al*. (2024).

Scientific Research: investment in R&D is a key driver in addressing environmental issues, particularly when it comes to reducing pollution emissions. Funding allocated to research and development (R&D) catalyzes environmental progress. Governments frequently channel these financial resources into several critical areas, including; the advancement of eco-friendly technologies, enhancement of industrial processes for improved efficiency, and implementation of more effective pollution control strategies. This strategic allocation of R&D funds underscores the vital link between scientific progress and environmental stewardship. As Abdelwahab et al. (2024) highlighted in their study, such targeted investment in R&D plays a pivotal role in our collective efforts to combat environmental challenges. By fostering scientific breakthroughs and technological advancements, R&D expenditure becomes a powerful tool in our arsenal against environmental degradation, paving the way for a more sustainable future.

In general, we can say that although economic growth has historically been associated with increased emissions, the pathway is not deterministic. Policies that promote cleaner technologies, efficient resource use, and sustainable urban development can potentially decouple economic growth from NOx emissions.

As for the effect of built environment characteristics on NOx emissions, it is a crucial area of study in urban planning and environmental science. Here's an overview of this topic:

Urban population density typically correlates with pollution emissions. Higher-density areas often have increased traffic congestion, leading to higher vehicular emissions, Tsanakas (2019) and Borck and Schrauth (2021). However, compact urban forms can reduce travel distances, potentially decreasing overall emissions. The concept of the "compact city" or "city of short distances" has emerged as a prominent urban planning strategy with significant implications for NOx emissions. This model promotes relatively high residential density combined with mixed-use development, where various urban activities and infrastructure facilities are integrated within walkable distances. The compact city aims to create an intensified urban form that can potentially mitigate NOx emissions through several mechanisms: (1) Reduced Vehicle Dependency: By locating urban activities closer together, the compact city model encourages access to services and facilities via public transport, walking, and cycling. This reduction in automobile reliance can directly decrease NOx emissions from vehicular sources. (2) Efficient Infrastructure: The concentrated nature of compact cities allows for more efficient utility and infrastructure provision, potentially reducing energy consumption and associated NOx emissions.

Transportation Infrastructure: Road network design significantly impacts traffic flow and, consequently, pollutant emissions. Previous studies have shown that air pollution levels are significantly affected by road width and the proportion of roads in a given area, Habermann et al. (2015), Weichenthal et al. (2014), and Tang et al. (2013). Additionally, public transportation systems can reduce private vehicle use, leading to lower pollutant emissions. Bike lanes and pedestrian-friendly infrastructure can encourage non-motorized transport, further reducing emissions.

The subsequent sections are structured as follows: Section 2 outlines the study's methodology and the sources of data. Section 3 highlights the key findings of our analysis, including statistical outcomes. Section 4 offers a comprehensive discussion of our empirical results, contextualizing them within the existing literature and exploring their implications. Section 5 presents the limitations of our study. The final section summarizes the main conclusions drawn from our study and proposes evidence-based recommendations for policymakers and future research directions.

2. METHODS

2.1. Data Description

To model Provincial NOx emissions, particularly in China, we include eight main explanatory variables across 31 geographical regions for the year 2022, noting that data for Taiwan, Hong Kong, and Macao is unavailable. This information is derived from the China Statistical Yearbooks, published by the National Bureau of Statistics of China. For a general overview of our data, Table 1 presents the descriptive statistics for these variables.

According to Table 1, NOx emissions in China exhibit a mean of 290.5 thousand tons, with a substantial standard deviation of 187.7 thousand tons. Looking more closely at the raw data, regional variations were evident in this regard. At the lower end of the spectrum, Hainan province reports emissions of 34.9 thousand tons, while Shandong province tops the list with 769.6 thousand tons. This stark contrast in emissions levels points to considerable regional differences in factors influencing NOx production.

The observed variation may be attributed to the diverse stages of economic development across China's regions, a hypothesis central to our study. This conjecture is further supported by the

Table 1: Descriptive statistics and variable definitions

Dimension	Variable name		Measuring unit	Average value	Standard deviation	Minimum value	Maximum value
Dependent	Y	NOx Emissions in Wast Gas	thousand metric tons	290.5	187.7	34.9	769.6
Socio-economic factors	X_1	Electricity Consumption	billion kWh	278.6	202.9	11.9	787.0
	X_2	PCEXP	thousand yuan	24	7.7	15.9	46.0
	X_3	R&D Expenditure	billion yuan	62.5	79.9	0.2	321.8
Environmental and land use factors	X_4	Numbers of Vehicles in Operation	thousand unit	22.7	16.7	0.9	66.6
	X_5	Urban Population Density	thousand Pearson/sq.km	3.1	1	1.5	5.4
	X_6	Green-covered Area	% of Completed Area	42.3	2.8	36.2	49.8
	X_7	Land Used for urban, Rural, Industrial, and Mining Activities	million hectares	1.2	0.7	0.2	2.9
	X_8	Cultivated Land Area	million hectares	4.1	3.6	0.1	17.1

marked differences in the explanatory variables among these regions. Our research aims to delve deeper into these regional disparities, examining how economic growth trajectories and other factors contribute to the varying levels of NOx emissions. By understanding these relationships, we hope to shed light on potential strategies for mitigating emissions while accounting for regional economic contexts.

2.2. Spatial Visualization of NOx Emissions across Chinese Regions

Figure 1 illustrates an exploration of the spatial distribution of NOx emissions across 31 provinces in China for the year 2022. The map employs a color gradient to illustrate varying emission levels across provinces. Cooler colors (shades of blue) represent lower emission intensities, while warmer colors (shades of red) indicate higher levels.

This spatial visualization reveals a distinct geographical pattern of NOx emissions in China. "Hot spots," characterized by the accumulation of high emissions, are predominantly clustered in the eastern and northern regions of the country. Provinces such as Shandong, and Hebei emerge as significant contributors to these elevated emission levels. In contrast, "cold spots" or low-emission cluster areas are primarily situated in the southern, southwestern, and northwestern regions. Hainan, Tibet, and Qinghai stand out as notable examples of these low-emission zones. This spatial distribution may indicate the possibility of regional interdependencies in NOx emissions across China. The clear demarcation between high and low-emission areas points to underlying socioeconomic, industrial, or geographical factors influencing pollution levels. Given these findings, it is necessary to focus on targeted pollution control measures in specific high-emission cluster areas. At the same time, proactive strategies should be developed and implemented to reduce the emergence of new high-emission areas.

2.3. Spatial Regression Models

NOx air pollutants in China generally display spatial dispersion patterns. This spatial dependence among neighboring regions indicates the necessity for SRMs that can incorporate interactions between various spatial units. Spatial econometrics identifies three main types of interaction effects: (a) spatial lag of dependent variable [equation (1)], where the value of the dependent variable in one location is influenced by the values of the same variable in neighboring locations; (b) spatial autocorrelation of error term [equation (2)], indicating correlated residuals across locations; (c) spatial lag of independent variables [equation (3)], where predictors in one area are affected by those in surrounding areas. In the modeling process, the first step researchers should take is to assess the presence of spatial effects in their data and, if confirmed, identify which interaction type(s) to consider. These effects can occur individually or in combination, as detailed in Table A1 (in Appendix). For a visual representation, refer to Figure A1 (In Appendix). For more detailed information on these concepts, the works of Youssef et al. (2020) and Elhorst (2014).

To address the first type of spatial interaction effects, we can use the spatial lag model (SLM), which assumes that the dependent variable of the unit is directly influenced by the spatially weighted dependent variable of neighboring units, Rüttenauer (2022). In the SLM, labeled spatial autoregressive (SAR) model or a mixed regressive SAR model, spatial autocorrelation is incorporated through a spatial lag of the dependent variable. Suppose we have spatial units or locations in our analysis. The SLM can be expressed as:

$$y_n = \lambda_0 W_n y_n + X_n \beta_0 + \varepsilon_n \tag{1}$$

$$\varepsilon_n \sim iid(0, \sigma^2 I_n)$$

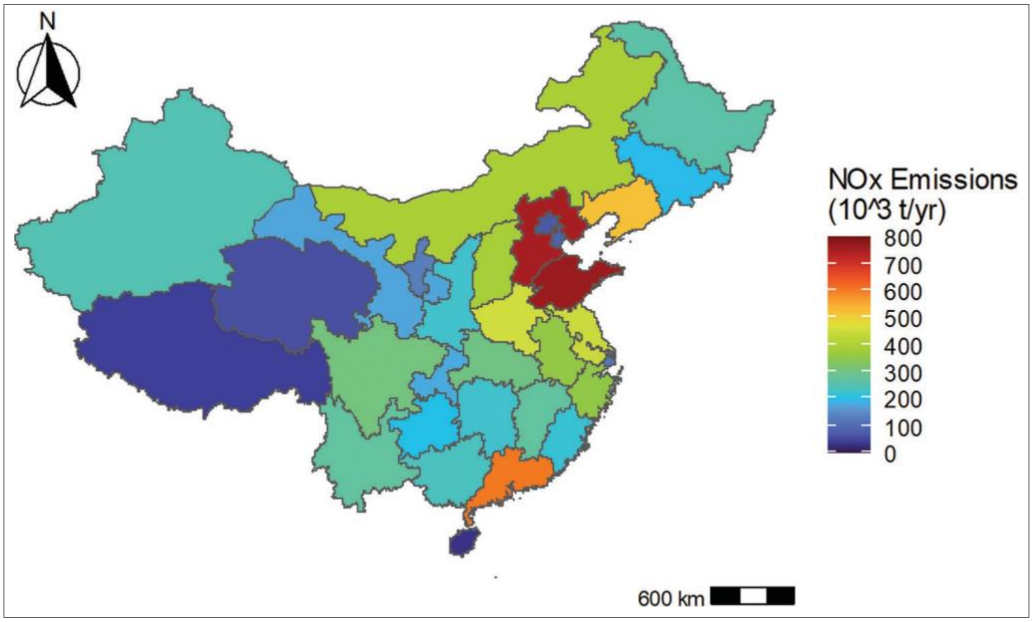
Where n denotes the number of locations or spatial units, y_n is an $(n\times 1)$ vector containing the values of the dependent variable across all locations, λ_0 is the SAR parameter, W_n is an $(n\times n)$ spatial weight matrix composed of non-negative elements. This matrix plays a crucial role in spatial econometrics by quantifying the spatial relationships and connectivity between different locations in the dataset. $W_n y$ indicates to the endogenous interaction effects, X_n is an $(n\times K)$ matrix of exogenous independent variables, K is the number of independent variables, β_0 is a $(K\times 1)$ vector of parameters associated with the explanatory variables in X, ε_n is an $(n\times 1)$ vector of disturbances, i.e., $\varepsilon_n \sim (0, \sigma^2 I_n)$, and I_n is an $(n \times n)$ identity matrix.

In addition to the SLM, the spatial error model (SEM) is used to address the second type of spatial interaction. The SEM can be specified as:

$$y_n = X_n \beta_0 + \varepsilon_n$$

$$\varepsilon_n = \rho_0 W_n \varepsilon_n + v_n \tag{2}$$

Figure 1: Provincial NOx emissions distribution in 2022



Where ρ_0 represents a spatial autocorrelation parameter, and v_n denotes a spatially uncorrelated disturbance. In this specification, we assume that the spatial correlation among units is caused by unobserved characteristics, which are either spatially clustered or follow a spatial pattern, independent of the included covariates.

To capture the third type of spatial interaction effects, we can utilize the spatial lag of X model (SLX). This specification examines the exogenous spatial interactions by incorporating $W_n X_n$, as extra independent variables to the traditional multiple regression equation. The SLX can be specified as:

$$y_n = X_n \beta_0 + W_n X_n \gamma_0 + \varepsilon_n \tag{3}$$

Where γ_0 is analogous to β_0 of order (K×1). The indirect spatial effects in this model are quantified by the parameter estimates, γ_0, corresponding to the $W_n X_n$ variables. In contrast, the direct effects are captured by the traditional parameter estimates, β_0, corresponding to the X_n variables.

Each model addresses different aspects of spatial dependence, allowing researchers to select the most appropriate approach based on the nature of their data and research questions.

2.4. Spatial Regression Models Assumptions

Even though there are different SRMs specifications, there are some basic common features for all of them, including:

A1. Assumptions of Spatial Weights Matrices:
- [1] All spatial weights matrices, i.e., W_n are non-stochastic matrices with zero diagonals.
- [2] The spatial transformation matrices, i.e., (I_n-λW_n) are invertible on the compact parameter spaces of spatial parameters λ and ρ.
- [3] The admissible parameter space for the true spatial parameters λ and ρ is[-1, 1].

A2. Assumptions of the Error Components: The relevant disturbances, i.e. $\{\varepsilon_i\}$, $i = 1,...,n$ are *iid* across *i* with zero mean and finite variance.

A3. Assumptions on Covariates: The regressors X_n are non-stochastic and have full column rank and their elements are UB in absolute value.

These assumptions are frequently made in spatial econometrics; Kelejian and Robinson (1998), and Lee (2004), among others.

2.5. Our Empirical Framework

This section outlines the methodological framework supporting our research and demonstrates a thorough decision-making process crafted to facilitate the selection of the optimal model for spatial analysis. The key procedural steps encompass:

- [1] Estimate OLS Regression Model.
- [2] Diagnose multicollinearity among independent variables to ensure the model's robustness and accuracy.
- [3] Construct the spatial weights matrices to incorporate spatial interactions and enhance the spatial analysis framework.
- [4] Capture the type of spatial interaction using classical and robust Lagrange Multiplier (LM) tests for each spatial weights matrix.
- [5] Evaluate model fit by calculating the goodness of fit criteria alongside a comprehensive assessment of the Likelihood ratio (LR) test, the Wald test, and the coefficients' significance for all nominated models.
- [6] Assess the presence of heteroscedasticity in the error term of the chosen model by the Breusch-Pagan test, ensuring the model's statistical integrity.

2.6. Multicollinearity Diagnostics

To avoid inaccurate statistical inferences, we diagnosed the multicollinearity problem before modeling the linear equations as mentioned in step 2 in our empirical framework above. The consequences of this issue include inaccurate estimates, inflated standard errors, misleading p-values, diminished significance in partial t-tests, and reduced predictive power of the model, Abonazel et al. (2024) and Abdelwahab et al. (2024).

We employ two primary tools to detect multicollinearity: Pearson's correlation matrix and the Variance Inflation Factor (VIF), Guo et al. (2022) and Abonazel and Shalaby (2021). As a rule of thumb, VIF values exceeding 5 warrant closer examination, while those surpassing 10 indicate severe multicollinearity that requires corrective measures.

2.7. Construction of Spatial Weights Matrix

Our study explores the nuances of spatial relationships using two distinct approaches of constructing weight matrices to evaluate the matrix density impact on empirical inference.

[a] The K-nearest Neighbor Matrix (KNNM): the KNNM establishes the spatial relationships between different locations based on their proximity. In this setup, each location is connected to its (K) nearest neighbors, where K is a pre-specified number. This ensures that every location has exactly K connections, regardless of the actual distances involved. In our analysis, we have chosen (K = 6). For a binary KNNM, The spatial weights matrix element w_{ij}, is predefined as:

$$w_{ij} = \begin{cases} 1 \text{ if } d_{ij} \le d_{i(k)} & \forall i \ne j \text{ and } i, j = 1, \ldots, n \\ 0 & \text{otherwise} \end{cases} \quad (4)$$

Where d_{ij} represents the distance between the locations (i) and (j), and $d_{i(k)}$ refers to a critical distance threshold (distance to the Kth nearest neighbor). The KNNM structure offers simplicity in interpreting spatial relationships. Nevertheless, its primary limitation is that it disregards distance intensity. For example, with a 1 km influence distance, a unit 10 meters away would have the same weight as one 1 km away. Dubé and Legros (2014) point out that this limitation becomes evident when comparing weights across various distances. This equal weighting, regardless of actual proximity, may not accurately represent the true spatial dynamics in some cases.

[b] The Gaussian Transformation Matrix (GTM): this structure offers a key advantage through its utilization of the Gaussian function outlined in equation (5), which assigns higher weights to spatial units that are closer together and lower weights to those that are farther apart.

$$w_{ij} = \begin{cases} \left[1 - \left(d_{ij}/d\right)^2\right]^2 & \text{if } d_{ij} \le d \quad \forall i \ne j \text{ and } i, j = 1, \ldots, n \\ 0 & \text{if } d_{ij} > d \text{ or } i = j \end{cases} \quad (5)$$

Here, the critical distance d plays a crucial role, with selecting the optimal value being a primary challenge to address. In this context, $d = Max\left(\min\left(d_{ij}\right)\right)$ is computed as 1199. The distances between the centroids of Chinese regions are sourced from "Map Developer" see Table 2. To enhance the matrix interpretability, row standardization is conducted using the approach detailed by Lottmann (2012).

3. RESULTS

3.1. Multicollinearity Tests

Before we begin estimating spatial regression models, we must test for multicollinearity. Table 3 shows the correlation matrix between the explanatory variables and the values of the VIF for each explanatory variable.

Table 3 reveals strong correlations (>0.89) between variables "X_3" as well as "X_4" with two others. Initial Variance Inflation Factor (VIF1) results confirm multicollinearity among these regressors. Following Paul's (2006) recommendation to remove variables with high VIF values, we removed "X_3" and "X_4" from the model. Subsequent VIF calculations (VIF2) show no multicollinearity, with all values below 10. As a result, we can proceed with our analysis using the remaining 6 explanatory variables.

3.2. Spatial Dependence Tests

Robust Lagrange Multiplier tests (RLM), along with the classical ones (CLM), are conducted to examine the spatial structure of NOx emissions, following the methodologies of Anselin et al. (1996), Anselin (1988), and Burridge (1980). The results presented in Table 4, reveal that there is no significant spatial error in the data for either weights matrix. As a result, we can omit the spatial error term from our subsequent analysis.

We then utilize the LR test to evaluate whether the SDM can be reduced to the SLM. This test compares two related models, where one is a constrained version of the other. In our analysis, the SDM encompasses the SLM. The findings in Table 5 indicate that the LR test statistic is significant at a 5% level for the KNNM and a 10% level for the GTM. These results suggest that the SDM provides a notably superior fit compared to the SLM. Consequently, we conclude that reducing the SDM to the SLM is not appropriate in any of the scenarios examined.

3.3. Model Selection

The estimation results are presented in Table 6. We assessed the nominated models using several criteria, including Pseudo R^2, log-likelihood function (LLF), sigma, the Bayesian and the Akaike information criteria (BIC and AIC). Our evaluation reveals that the SDM utilizing the KNNM performs better than the one using the GTM. Specifically, the SDM with KNNM show higher R^2 and LLF values, as well as lower sigma and AIC values. These results indicate that incorporating the KNNM in the SDM enhances the model's explanatory power and its capacity to account for spatial variations in NOx emissions.

3.4. Heterogeneity Diagnoses

To assess the heteroscedasticity's presence in the KNNM-based SDM error term, we employed The Breusch-Pagan test, following the methodology outlined in Atikah et al. (2021).

As shown in Table 7, the test produced a P-value greater than the standard significance level of 0.05. This result means we cannot reject the null hypothesis, which suggests that the error terms are homoscedastic. Therefore, we conclude that the KNNM-based

Table 2: Descriptive statistics of the distances between centroids in Chinese regions (in kilometers)

Average Distances		Standard Deviation of Distances	Minimum Distance	Maximum Distance
1450		761	104	3739
Links		**Number of Nonzero Links**	**% of Nonzero Weights**	**The Average Number of Links**
Spatial structure	KNNM	186	19.35	6
	GTM	396	41.2	12.8

Table 3: Pearson correlation matrix and VIF

	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8
X_1	1							
X_2	0.3766	1						
X_3	0.8648	0.5940	1					
X_4	0.9084	0.4300	0.8968	1				
X_5	−0.1149	0.0888	−0.0418	0.0291	1			
X_6	0.4085	0.0095	0.3679	0.3837	−0.1992	1		
X_7	0.7816	−0.0200	0.5452	0.7882	0.0243	0.3766	1	
X_8	0.1289	−0.3280	−1.222	0.1073	0.1073	−0.0964	0.4863	1
VIF1	9.67	2.36	11.86	16.21	1.24	1.41	9.39	2.05
VIF2	5.23	1.88	---	---	1.19	1.39	5.48	1.88

"VIF1" is the VIFs for all regressors in the study, while "VIF2" is the VIFs calculated after excluding "X3 and X4" from the analysis

Table 4: Results of classical and robust LM tests across various spatial structures

Test spatial structure	CLM		RLM	
	Lag	Error	Lag	Error
KNNM	3.0786*	0.4778	3.1202*	0.5194
GTM	5.4439**	0.3497	6.6513***	1.5571

The symbols ***, **, and * indicate significance at the 0.1%, 1%, and 5% levels, respectively

Table 5: Results of the LR tests across various spatial structures

Spatial structure	Hypothesis	LRchi2 (6)	P-value
KNNM	SLM nested in SDM	15.1170	0.0194
GTM	SLM nested in SDM	10.8880	0.0919

SDM has a well-specified error structure, enhancing our confidence in the model's parameter estimates' reliability and efficiency.

4. DISCUSSION

In the SDM, the traditional interpretation of regression coefficients fails to fully capture the model's complexity due to spatial interaction effects. The SDM's structure, with the dependent variable on both sides of the equation, requires a more sophisticated interpretation approach. To accurately understand the impacts of explanatory variables in an SDM, we must consider two types of effects: (1) direct effects which measure how a change in an explanatory variable in a specific location affects the dependent variable in that same location, and (2) indirect effects which capture how a change in an explanatory variable in one location influences the dependent variable in other locations, representing spatial spillovers. By calculating and interpreting both direct and indirect effects for each explanatory variable, we can gain a comprehensive understanding of the spatial relationships and influences within the model. For a more detailed exploration of these concepts and their application, interested readers are directed to the seminal works of LeSage and Pace (2009), Kopczewska et al. (2017), and Shalaby (2021). These sources provide in-depth guidance on properly interpreting and analyzing spatial econometric models, including SDM.

From the findings presented in Table 8, we can infer several conclusions, including: Electricity consumption has a complex relationship with NOx emissions which are characterized by distinct direct and indirect effects. Specifically, for everyone billion kWh increase in electricity consumption within a given region, there is a corresponding increase of about 367.3 tons of NOx emissions in that same region. This positive direct effect highlights the close relationship between electricity generation and NOx pollution. Many power plants, especially those using fossil fuels like coal or natural gas, emit NOx as a byproduct of the combustion process. As electricity consumption increases in a region, local power plants may need to increase production, leading to higher NOx emissions in that same region. Additionally, Regions with higher electricity consumption often have more intensive industrial activities, which can contribute to increased NOx emissions through both energy use and industrial processes.

Interestingly, the same one billion kWh increase in electricity consumption in one region is associated with a decrease of about 713.7 tons of NOx emissions in surrounding regions. This negative indirect effect could be explained by several factors: (a) Technological spillovers: High-consumption regions may invest more in advanced, cleaner technologies that eventually spread to neighboring areas, helping them reduce emissions, (b) Policy diffusion: Stricter environmental regulations in high-consumption areas may influence policy-making in neighboring regions, leading to adoption of cleaner practices, and (c) Economic specialization: Regions with high electricity consumption might focus on energy-intensive industries, allowing neighboring areas to specialize in less emission-intensive sectors.

These results are consistent with research conducted by the European Environment Agency, which recognized that NOx emissions are significantly affected by heat production and

Table 6: Results of the estimated SRMs across various spatial structures

Variable	KNNM			GTM		
	SLM	SEM	SDM	SLM	SEM	SDM
X_1	0.496 1***	0.4422***	0.3201**	0.4333***	0.4224***	0.4502***
X_2	−4.7346*	−3.6243	0.3224	−4.5688**	−4.5769*	−4.1508*
X_5	−10.5811	−5.6560	5.8032	−10.9692	−2.2659	−13.6412
X_6	1.4102	3.1188*	−3.5453	0.2731	3.6019**	1.6366
X_7	107.6646**	122.2070***	167.176***	132.8895***	127.4476***	129.3348***
X_8	1.7259	−1.0779	−1.9688	−0.4499	3.2737	−4.0192
$W_i \times X_1$	-----	-----	−0.8306	----	----	0.5521
$W_i \times X_2$	-----	-----	23.9775***	----	----	17.6418
$W_i \times X_5$	-----	-----	29.6240	----	----	−41.2521
$W_i \times X_6$	-----	-----	−13.1272**	----	----	−6.3775
$W_i \times X_7$	-----	-----	189.4728	----	----	−5.2179
$W_i \times X_8$	-----	-----	48.1104***	----	----	50.8773**
$\hat{\lambda}$	0.3379*	-----	−0.4735	0.4919***	----	−0.8905***
$\hat{\rho}$	-----	0.42027*	-----	----	0.6023***	----
Wald chi2 Test	610.1141***	277.3299***	1030.306***	671.1170***	220.1989***	996.9256***
Pseudo R^2	0.8283	0.8189	0.8945	0.8404	0.8212	0.8877
LLF	178.3083	179.1330	−170.7496	−177.1387	−178.9009	−171.6949
Sigma	75.5560	77.2040	58.976	72.3740	75.97	59.6860
BIC	384.0885	385.7379	389.575	381.7492	385.2737	391.4656
AIC	372.6166	374.2660	369.4992	370.2773	373.8018	371.3898

The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively

Table 7: Results of Breusch-Pagan test of SDM based on KNNM

Null hypothesis (H_0)	Test statistic	P-value
The error terms are homoscedastic	8.4560	0.672

Table 8: Direct and indirect effects of KNNM-based SDM

Variable	Direct Effects	Indirect Effects
X_1	0.3673***	−0.7137*
X_2	−0.8236	17.3146**
X_5	4.5104	19.5322
X_6	−2.9946	−8.3201
X_7	161.870***	80.1689
X_8	−4.3278	35.6417***

The symbols ***, **, and * indicate the significance at 1%, 5% , and 10% levels, respectively

public electricity. The European Environment Agency also stated that nitrogen oxide emissions could decrease by up to 59% if advanced technologies were adopted to improve the environmental performance of large combustion plants, Lodewijks et al. (2013) and Abdelwahab et al. (2024). China has also recognized the need to address NOx emissions from electricity generation. In November 2011, the country introduced an electricity price subsidy (EPS) policy aimed at encouraging coal-fired power plants to install denitrification units. This policy represented a significant step towards reducing NOx emissions in the power sector.

The research by Lin et al. (2021) provides valuable insights into the effectiveness of China's Environmental Protection System (EPS) policy on NOx emissions and removal rates. Their study, which analyzed data from 113 prefectural-level cities from 2008 to 2015, revealed two key findings: (a) NOx emission reduction: the EPS policy resulted in a significant 1.1% decrease in NOx emissions, and (b) NOx removal improvement: for each additional power plant, there was a 2.8% increase in NOx removal (the amount of NOx treated and not released into the atmosphere). These findings highlight the effectiveness of targeted policies in addressing environmental challenges. The EPS policy demonstrates how economic incentives can drive technological adoption and environmental improvement in the power sector. The alignment between our findings and these broader studies underscores the complex relationship between electricity consumption and NOx emissions. It suggests that while increased electricity use can lead to higher local emissions, it can also drive innovations and policy changes that result in overall emission reductions when considering wider regional effects. This complexity emphasizes the need for nuanced, multi-faceted approaches to environmental policy-making, especially in rapidly developing economies like China.

PCEXP demonstrates no significant direct impact on NOx emissions within the same area. However, it exhibits a substantial positive indirect influence on NOx emissions in neighboring regions. The absence of a significant direct effect suggests that changes in PCEXP within a specific region do not have a measurable impact on NOx emissions in that same region. This could indicate that: (a) Household consumption patterns may not be directly linked to major NOx-emitting activities within the same area, (b) Local regulations or technologies might be effectively mitigating any potential direct impacts of increased household consumption on NOx emissions, and (c) The composition of household expenditure might not significantly affect NOx-intensive sectors in the local economy.

On the other hand, the presence of a significant positive indirect effect implies that an increase in household consumption expenditure in one region is associated with an increase in NOx emissions in surrounding regions. This could be explained by several factors: (a) Economic spillovers and supply chain effects: Increased demand for goods and services in one region could lead to increased production in neighboring areas, especially if these areas specialize in manufacturing or other NOx-emitting industries, and (b) Transportation impacts: Higher consumption might lead to increased transportation of goods between regions, resulting in higher NOx emissions from vehicles in surrounding areas.

Higher levels of PCEXP are associated with lower NOx emissions. PCEXP in a given region also has a significant positive effect on NOx emissions in neighboring regions. These results are consistent with research by Zhang et al. (2019b), which suggests that economic development may initially hinder NOx emission reduction until a critical threshold is exceeded, after which emissions begin to decline. This phenomenon can be explained by the tendency of regions with high PCEXP and strong economic growth to implement effective measures or adopt technologies that effectively reduce NOx emissions.

The positive significant direct effect of X_7 indicates that changes in land used for urban, rural, industrial, and mining activities within a specific region have a measurable and statistically significant impact on NOx emissions in that same region. A one million hectares increase in land used for urban, rural, industrial, and mining activities within a specific region leads to an increase of approximately 161.9 thousand tons of NOx emissions in the same region. This suggests a strong, immediate connection between these land use types and NOx pollution. Where (a) Urban areas associated with high population density, increased vehicle traffic, and concentrated energy consumption, and may include NOx sources like residential heating, commercial activities, and urban transportation systems, in this context, Liu et al. (2015) demonstrated urbanization has a substantial effect on urban meteorology. It can alter the atmospheric diffusion capability in urban areas and therefore affect pollutant concentrations. (b) Rural activities encompass a diverse range of activities that can contribute to NOx emissions through various mechanisms. These can be broadly categorized into two main types: agricultural activities, which may use NOx-emitting equipment or fertilizers, Skiba et al. (2021), and a broader range of rural land uses, such as livestock farming, rural industries, and small-scale manufacturing, etc., (c) Industrial activities likely be a major contributor, including factories, power plants, and other industrial facilities, additionally, industrial processes often involve high-temperature combustion, a primary source of NOx Zhang et al. (2019b), (d) Mining activities involve heavy machinery, explosives, and energy-intensive processes, and can contribute significantly to NOx emissions through both operations and associated transportation, Oluwoye et al. (2017).

An intriguing finding is that area cultivated land has no direct effect but has a positive significant indirect effect on NOx emissions, which requires careful interpretation. The absence of direct effect means that changes in the area of cultivated land within a specific region do not significantly impact NOx emissions in that same region. This could be due to several factors: (a) Modern agricultural practices in the region might be using low-emission technologies or methods, (b) The direct emissions from cultivated land (e.g., from fertilizer use or agricultural machinery) might be relatively small compared to other sources of NOx in the same region, (c) There could be effective local policies or practices in place that mitigate direct NOx emissions from agricultural activities.

On the other hand, a significant positive indirect effect indicates that an increase of 1 million ha in the area of cultivated land in one region is associated with an increase of 35.6 thousand tons in NOx emissions in neighboring regions. This spatial spillover effect could be explained by several mechanisms: (a) Agricultural supply chain: Increased cultivation in one area might lead to increased processing, transportation, and related industrial activities in neighboring regions, which could contribute to higher NOx emissions, (b) Economic spillovers: Greater agricultural production might stimulate overall economic activity in surrounding areas, potentially leading to increased industrial output or energy consumption, and consequently higher NOx emissions, (c) Land used changes: Expansion of cultivated land in one area might lead to the displacement of other activities (e.g., industry, urbanization) to neighboring regions, indirectly increasing their NOx emissions, (d) Regional specialization: As one area focuses more on agriculture, neighboring regions might specialize in complementary industries that are more NOx-intensive.

5. LIMITATIONS

The research on NOx emissions in China, while informative, faces several limitations that warrant discussion, including (1) Temporal scope: The study is constrained to data in 2022, offering only a snapshot of the situation rather than a comprehensive temporal analysis. This limitation is due to gaps in time series data across all regions, preventing the examination of long-term trends or year-to-year variations in NOx emissions and their driving factors. Consequently, the research may not capture important historical patterns, cyclical fluctuations, or the evolution of relationships between socioeconomic factors and emissions over time. Spatial panel data analysis could provide more comprehensive insights into the evolution of NOx emissions in China. (2) Spatial resolution: The study likely uses provincial or city-level data, which may mask intra-regional variations in emissions and socioeconomic factors. Finer spatial resolution (e.g., county or district level) could reveal more nuanced patterns and relationships. (3) Limited variables: The study focuses on specific socioeconomic factors, potentially overlooking other important variables such as industrial composition, transportation patterns, or policy interventions. Including a broader range of variables could provide a more comprehensive understanding of NOx emission drivers. (4) Lack of sector-specific emissions data: The study is limited by the unavailability of detailed NOx emissions data from main economic sectors in 2022. This data gap impairs the ability to pinpoint the most significant polluting industries and hampers the development of targeted, sector-specific recommendations for emissions reduction. The absence of this granular information may result in overly generalized mitigation strategies, potentially diminishing their effectiveness in addressing the primary sources of NOx emissions.

6. CONCLUSIONS

Environmental pollution, particularly NOx emissions, presents a significant challenge intrinsically linked to economic development. China, as a rapidly growing economy, faces the complex task of balancing progress with environmental sustainability. This situation necessitates in-depth research into the socio-economic drivers of NOx emissions in the country. Our study employs SRMs to analyze a comprehensive geographical dataset covering 31 Chinese regions in 2022. This approach emphasizes the critical role of spatial dependencies in understanding and accurately modeling NOx emissions. Our research yields several key insights:

Our analysis reveals that NOx emissions in China exhibit complex spatial patterns, demonstrating both spatially lagged-dependent and lagged-independent correlations. This finding underscores the interconnected nature of environmental pollution across regions and highlights the importance of considering spatial relationships in environmental modeling.

Among the SRMs evaluated, the KNNM-based SDM emerged as the most suitable for capturing these spatial effects. This conclusion is supported by rigorous statistical testing, including LM and LR tests, as well as comprehensive goodness-of-fit criteria.

Electricity consumption demonstrates a nuanced impact, with increased consumption leading to higher local NOx emissions but potentially reducing emissions in neighboring regions. This suggests that while local energy use contributes to pollution, it may also drive technological and policy innovations that benefit wider areas. These findings suggest that policies aimed at reducing NOx emissions should: (a) Focus on improving energy efficiency and cleaner production in high-consumption regions to mitigate direct effects. (b) Facilitate technology transfer and policy learning between regions to maximize beneficial spillover effects.
(c) Consider the interconnected nature of regional economies and energy systems when designing interventions.

PCEXP shows no significant direct effect on local NOx emissions but has a positive indirect effect on emissions in surrounding regions. This indicates that consumer behavior in one area can have far-reaching environmental consequences beyond its immediate vicinity. To alleviate this impact, policymakers in China should focus on (a) encouraging interregional collaboration to develop coordinated strategies that account for the indirect effect of household consumption on NOx emissions by establishing platforms for sharing best practices and implementing joint initiatives that promote sustainable consumption patterns, and
(b) emphasizing sustainable practices across supply chains to mitigate the environmental footprint of increased production driven by consumer demand, and encouraging transparency and accountability in production processes to reduce emissions associated with manufacturing and transportation.

Land used for urban, rural, industrial, and mining activities has a significant direct effect on NOx emissions, underscoring the importance of spatial planning in pollution control. Interestingly, the cultivated land area shows no direct effect but a positive indirect effect on NOx emissions in neighboring regions. This suggests that agricultural practices may have more complex, spatially distributed impacts on air quality than previously thought. Given these results, it is imperative to formulate a comprehensive land use planning framework. This strategy should entail targeted emission reduction measures tailored to the specific characteristics of each land use type. Emphasize eco-friendly practices in urban areas to address high-density populations and vehicular emissions, promote sustainable agricultural techniques in rural regions to reduce fertilizer-related NOx sources, and implement sustainable practices in mining activities to mitigate NOx-intensive operations. Furthermore, considering the significant indirect effect of cultivated land on NOx emissions, focus on collaborative regional approaches to address spatial spillover effects. Implement cross-boundary policies that regulate agricultural supply chains, promote sustainable economic growth, manage land use changes effectively, and encourage regional specialization to minimize indirect NOx emissions from increased cultivated land areas.

Interestingly, the urban population density and % green-covered area don’t show significant impacts on NOx emissions in Chinese regions.

In conclusion, this research underscores the need for comprehensive, spatially-aware approaches to environmental management. Policymakers should consider both local and regional impacts when designing strategies to reduce NOx emissions. Future research should further explore the mechanisms behind these spatial relationships to inform more effective environmental policies in rapidly developing economies like China.

REFERENCES

Abdelwahab, M.M., Shalaby, O.A., Semary, H.E., Abonazel, M.R. (2024), Driving factors of NOx emissions in China: Insights from spatial regression analysis. Atmosphere, 15(7), 793.

Abonazel, M.R., Alzahrani, A.R.R., Saber, A.A., Dawoud, I., Tageldin, E., Azazy, A.R. (2024), Developing ridge estimators for the extended Poisson-Tweedie regression model: Method, simulation, and application. Scientific African, 23, e02006.

Abonazel, M.R., Shalaby, O. (2021), On labor productivity in OECD countries: Panel data modeling. WSEAS Transactions on Business and Economics, 18(2), 1474-1488.

Anselin, L. (1988), Spatial Econometrics: Methods and Models. Dorddrecht: Kluwer Academic Publishers.

Anselin, L., Bera, A.K., Florax, R., Yoon, M.J. (1996), Simple diagnostic tests for spatial dependence. Regional Science and Urban Economics, 26(1), 77-104.

Atikah, N., Widodo, B., Rahardjo, S., Kholifia, N., Afifah, D.L. (2021), The efficiency of Spatial Durbin Model (SDM) parameters estimation on advertisement tax revenue in Malang City. Journal of Physics: Conference Series, 1821(1), 012012.

Borck, R., Schrauth, P. (2021), Population density and urban air quality. Regional Science and Urban Economics, 86, 103596.

Burridge, P. (1980), On the Cliff□Ord test for spatial correlation. Journal of the Royal Statistical Society: Series B (Methodological), 42(1), 107-108.

Cardinale, R., Cardinale, I., Zupic, I., (2024) The EU s vulnerability to gas price and supply shocks: The role of mismatches between policy beliefs and changing international gas markets. Energy Economics, 131, 107382.

Demena, B.A., Afesorgbor, S.K. (2020), The effect of FDI on environmental emissions: Evidence from a meta-analysis. Energy Policy, 138, 111192.

Diao, B., Ding, L., Su, P., Cheng, J. (2018), The spatial-temporal characteristics and influential factors of NOx emissions in China: A spatial econometric analysis. International Journal of Environmental Research and Public Health, 15(7), 1405.

Dubé, J., Legros, D. (2014), Spatial Econometrics Using Micro-Data. United States: John Wiley and Sons.

Elhorst, J.P. (2014), Spatial panel models. In: Handbook of Regional Science. Heidelberg, Berlin: Springer.

Gill, A.R., Viswanathan, K.K., Hassan, S. (2018), The environmental Kuznets curve (EKC) and the environmental problem of the day. Renewable and Sustainable Energy Reviews, 81, 1636-1642.

Grossman, G., Krueger, A. (1991), Environmental Impacts of a North American Free Trade Agreement. National Bureau of Economic Research Working Paper No 3914.

Guo, M., Chen, S., Zhang, Y. (2022), Spatial analysis on the role of multi-dimensional urbanizations in carbon emissions: Evidence from China. International Journal of Environmental Research and Public Health, 19(9), 5315.

Habermann, M., Billger, M., Haeger-Eugensson, M. (2015), Land use regression as method to model air pollution. Previous results for Gothenburg/Sweden. Procedia Engineering, 115, 21-28.

Han, C., Gu, Z., Yang, H. (2021), EKC test of the relationship between nitrogen dioxide pollution and economic growth-A spatial econometric analysis based on Chinese city-data. International Journal of Environmental Research and Public Health, 18(18), 9697.

He, C., Xiang, P., Jiang, K. (2023), Clean coal technologies: Transition to a low emission future. In: Handbook of Air Quality and Climate Change. Singapore: Springer Nature, p. 1301-1332.

Kelejian, H.H., Robinson, D.P. (1998), A suggested test for spatial autocorrelation and/or Heteroskedasti city and corresponding Monte Carlo results. Regional Science and Urban Economics, 28(4), 389-417.

Kharbach, M., Chfadi, T. (2017), CO_2 emissions in Moroccan road transport sector: Divisia, Cointegration, and EKC analyses. Sustainable Cities and Society, 35, 396-401.

Kopczewska, K., Kudła, J., Walczyk, K. (2017), Strategy of spatial panel estimation: Spatial spillovers between taxation and economic growth. Applied Spatial Analysis and Policy, 10(1), 77-102.

Lee, L.F. (2004), Asymptotic distributions of quasi□maximum likelihood estimators for spatial autoregressive models. Econometrica, 72(6), 1899-1925.

LeSage, J.P., Pace, R.K. (2009), Introduction to Spatial Econometrics. New York: Chapman and Hall/CRC.

Levinson, A., Taylor, M.S. (2008), Unmasking the pollution haven effect. International Economic Review, 49(1), 223-254.

Lin, C., Shao, S., Sun, W., Yin, H. (2021), Can the electricity price subsidy policy curb NOX emissions from China's coal-fired power industry? A difference-in-differences approach. Journal of Environmental Management, 290, 112367.

Liu, H., Ma, W., Qian, J., Cai, J., Ye, X., Li, J., Wang, X. (2015), Effect of urbanization on the urban meteorology and air pollution in Hangzhou. Journal of Meteorological Research, 29(6), 950-965.

Lodewijks, P., Pieper, H., Van Wortswinkel, L., Boyce, B., Adams, M., Goossens, E. (2013), Reducing air Pollution from Electricity-generating Large Combustion Plants in the European Union. An aSSESSMENT of Potential Emission Reductions of NOx, SO_2, and Dust. EEA Technical Report No 9/2013. Denmark: European Environment Agency.

Lottmann, F. (2012), Explaining Regional Unemployment Differences in Germany: A Spatial Panel Data Analysis (No. 2012-026), SFB 649 Discussion Paper.

Mauro, M.R. (2024), Energy security, energy transition, and foreign investment: An evolving complex relationship. Laws, 13(4), 47-50.

Oluwoye, I., Dlugogorski, B.Z., Gore, J., Oskierski, H.C., Altarawneh, M. (2017), Atmospheric emission of NOx from mining explosives: A critical review. Atmospheric Environment, 167, 81-96.

Paul, R.K. (2006), Multicollinearity: Causes, Effects, and Remedies. New Delhi: IASRI, p58-65.

Poumanyvong, P., Kaneko, S. (2010), Does urbanization lead to less energy use and lower CO_2 emissions? A cross-country analysis. Ecological Economics, 70(2), 434-444.

Rüttenauer, T. (2022), Spatial regression models: A systematic comparison of different model specifications using Monte Carlo experiments. Sociological Methods and Research, 51(2), 728-759.

Shalaby, O. (2021), Some Estimation Methods of Spatial Panel Data Models. [Master Dissertation]. Egypt: Faculty of Graduate Studies for Statistical Research, Cairo University.

Skiba, U., Medinets, S., Cardenas, L.M., Carnell, E.J., Hutchings, N.J., Amon, B. (2021), Assessing the contribution of soil NOx emissions to European atmospheric pollution. Environmental Research Letters, 16(2), 025009.

Song, F., Mehedi, H., Liang, C., Meng, J., Chen, Z., Shi, F. (2021), Review of transition paths for coal-fired power plants. Global Energy Interconnection, 4(4), 354-370.

Tang, R., Blangiardo, M., Gulliver, J. (2013), Using building heights and street configuration to enhance intraurban PM10, NOx, and NO_2 Land use regression models. Environmental Science and Technology, 47(20), 11643-11650.

Tsanakas, N. (2019), Emission Estimation Based on Traffic Models and Measurements. Vol. 1835. Linköping, London: Linköping University Electronic Press.

Van Vuuren, D.P., Bouwman, L.F., Smith, S.J., Dentener, F. (2011), Global projections for anthropogenic reactive nitrogen emissions to the atmosphere: An assessment of scenarios in the scientific literature. Current Opinion in Environmental Sustainability, 3(5), 359-369.

Weichenthal, S., Farrell, W., Goldberg, M., Joseph, L., Hatzopoulou, M. (2014), Characterizing the impact of traffic and the built environment on near-road ultrafine particle and black carbon concentrations. Environmental Research, 132, 305-310.

Wu, B., Liu, C. (2023), Impacts of building environment and urban green space features on urban air quality: Focusing on interaction effects and nonlinearity. Buildings, 13(12), 3111.

Xiang, N., Li, S., Shu, C., Xu, F. (2024), Heavy industrial aggregation area's green transformation optimization pathways exploration with synergistic reduction pursues of CO_2 and gaseous pollutants. Journal of Environmental Management, 350, 119649.

Yan, J., Liu, C., Xiao, B., Wang, S. (2024), Environmental dynamics: Unraveling the nexus of air pollution, population agglomeration, and sustainable economic development in China: A provincial-level empirical analysis. Frontiers in Environmental Science, 12, 1349419.

Youssef, A.H., Abonazel, M.R., Shalaby, O.A. (2020), Determinants of per capita personal income in US states: Spatial fixed effects panel data modeling. Journal of Advanced Research in Applied Mathematics and Statistics, 5, 1-13.

Zhang, W.W., Sharp, B., Xu, S.C. (2019a), Does economic growth and energy consumption drive environmental degradation in China's 31 provinces? New evidence from a spatial econometric perspective. Applied Economics, 51(42), 4658-4671.

Zhang, Y., Shuai, C., Bian, J., Chen, X., Wu, Y., Shen, L. (2019b), Socioeconomic factors of PM2. 5 concentrations in 152 Chinese cities: Decomposition analysis using LMDI. Journal of Cleaner Production, 218, 96-107.

Zhou, Z., Zhou, Y., Ge, X. (2018), Nitrogen oxide emission, economic growth and urbanization in China: A spatial econometric analysis. In: IOP Conference Series: Materials Science and Engineering. Vol. 301. United States: IOP Publishing, p. 012126.

APPENDIX

Figure A1: Interaction effects between two locations

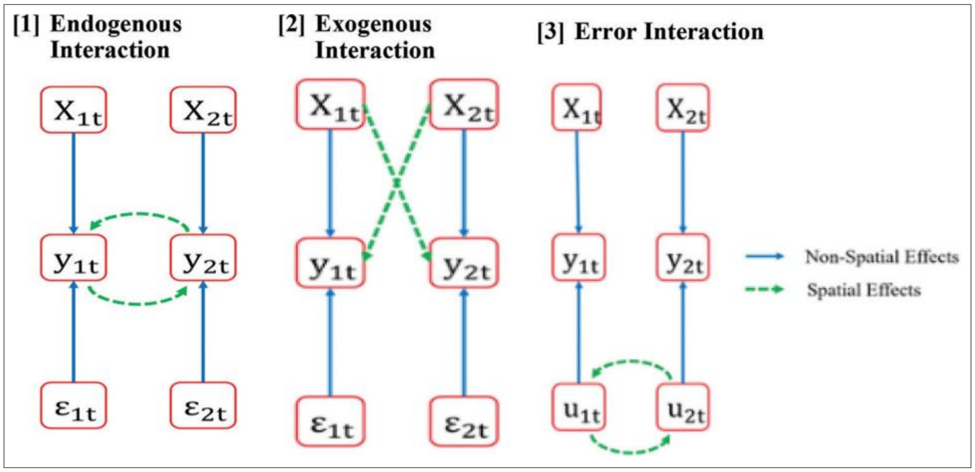


Table A1: All possible spatial interaction combinations in the SRMs

Model Name		Spatial Interactions	
		Term	**Count**
SLM	Spatial Lag Model	$W_n y_n$	1
SEM	Spatial Error Model	$W_n \varepsilon_n$	1
SLX	Spatial Lag of X Model	$W_n X_n$	K
SAC	Spatial Autoregressive Combined Model	$W_n y_n$ *and* $W_n \varepsilon_n$	2
SDM	Spatial Durbin Model	$W_n y_n$ *and* $W_n X_n$	K+1
SDEM	Spatial Durbin Error Model	$W_n X_n$ *and* $W_n \varepsilon_n$	K+1
GNS	General Nesting Spatial Model	$W_n y_n$ *and* $W_n X_n$ *and* $W_n \varepsilon_n$	K+2