

Is the Environmental Kuznets Curve Still Relevant in the Modern Context? – Insights From Air Pollutants in Chinese Cities

Jun Wang
Florida Atlantic University,
Boca Raton, USA
jwang3095@gatech.edu

Gulsah Akar
Georgia Institute of Technology
Atlanta, USA
gulsah.akar@design.gatech.edu

Shinah Park
Georgia Institute of Technology
Atlanta, USA
shinah.park@gatech.edu

This study investigated the presence of EKC-like relationships between various socioeconomic variables and air pollution indicators across 151 Chinese cities, analysed by quadratic regression models and geographic weighted regression (GWR) analysis. The results present critical insights into the applicability and limitations of the EKC. Only Air Quality Index, Nitrogen Dioxide (NO₂), and Fine Particulate Matter (PM_{2.5}) show statistically significant correlations with one socioeconomic variable, respectively, in an EKC-like pattern which is meaningful in reality. GWR coefficients serve as a diagnostic tool to identify those burdened cities where stricter emissions standards, greener industrial practices, or economic restructuring should be prioritized. The spatial dependencies challenge the EKC's assumption of isolated environmental-economic dynamics. Stricter environmental regulations in developed areas often lead to the displacement of polluting activities to regions with laxer standards. Policy efforts in tackling air pollution should focus on directly reducing emissions through localized, technology-based interventions rather than relying on economic growth to eventually improve air quality. Spatially targeted policies informed by city-specific patterns are essential, as pollution outcomes are shaped by regional industrial structures, population density, and cross-boundary spillover effects.

Key Words: air pollution, city development, geographic weighted regression, sustainable development, ecological development

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Introduction

Over the course of past industrial revolutions, human activities have had a growing impact on the environment. Thus, since the 1960s, the importance of environmental protection that mitigates negative effects from development, such as pollution, has gradually emerged into the spotlight.

Within this context, the Environmental Kuznets Curve (EKC) has been utilized to estimate the relationship between industrial development and the environment (Dinda 2004). First introduced by Grossman and Krueger (1991) as an application of the Kuznets Curve concept (Kuznets 1955), the EKC hypothesizes that as the economy grows, environmental damage increases at first but then eventually declines. This relationship can be used to assess the current status and estimate future pollution levels.

However, whether the Kuznets curve can explain the modern context has been debated by scholars from the early 2000s (Stern 2004; Guo and Shahbaz 2024). Stern (2004) discovered that developing countries began addressing environmental issues and adhering to the developed countries' standards before achieving high levels of per capita income. Additionally, many emerging technologies offer changes in pollutant types and pollution intensities (Wang et al. 2022; Wang et al. 2024), further complicating this discussion. Historically, research on the Kuznets Curve was mainly based on the context of industrialized countries in the West (Dasgupta et al. 2002). Therefore, there is a need to revisit this classic model considering the contemporary context.

China offers a valuable case for this analysis. It has developed a massive industrial system in a relatively short time, and the environmental impact brought by this rapid growth is clearly shown even over a limited time span (Luo et al. 2025; Song et al. 2012). China has not yet shown a significant tendency to move its industries abroad, indicating ongoing efforts to balance growth and environmental progress. The manufacturing industry accounted for 37.8% of China's GDP (National Bureau of Statistics of China 2016).

This research investigates the relationship between socioeconomic development and environmental pollution using Chinese cities as the study area. Our analyses focus on various air pollution indicators, such as Air Quality Index, Carbon Monoxide (CO), Nitrogen Dioxide (NO₂), Particulate Matter ≤ 10 micrometers in diameter (PM₁₀), Particulate Matter ≤ 2.5 micrometers in diameter (PM_{2.5}), and Sulfur Dioxide (SO₂),

and socioeconomic variables. Using global quadratic equations, we first explore whether the inverted U-shape is present in Chinese cities. We then further examine Geographically Weighted Regression results that consider spatial heterogeneity in relationships between the development indicators and air pollution intensities. We fill in the gap in the literature by providing granular city-level analysis to reveal hidden patterns that existing country-level panel EKC studies cannot do. Currently, city-level EKC analysis that considers spatial aspects is limited. Our study contributes to this discussion by comparing the global regression models and models with city-specific coefficients and providing insights on shaping future mitigation policies. There are large development disparities between different regions within China. Eastern, central, and western regions of China differ greatly in terms of per capita income, education level, and industry typologies, making China a good case for examining this literature gap (Long and Zhang 2011). The result will benefit policymakers in identifying the regions with high correlations between specific pollution components and the characteristics of the region, which helps prioritize mitigation strategies.

In the following sections, we discuss arguments in the literature and then introduce our data and methods. Next, we present our findings and interpret the results in the discussion section. Finally, we end by summarizing the main findings and room for future research.

Literature Review

This section is divided into three parts. The first section discusses the three phases of EKC theory, and the second introduces applications of worldwide and China-specific EKC analyses. In the third section, we will address how our study contributes to the existing EKC studies.

INTERPRETATION OF EKC THEORY

The Environmental Kuznets Curve is an inverted U-shape that represents three phases of economic development. The first phase is the pre-industrial economy with low income and lower levels of industry sector. In this first one-third of the whole phase, developments are driven by using natural resources with highly pollutant methods. Due to low awareness of the impacts of human activities on the environment, the pollution level rises (Kaika and Zervas 2013). The second phase is the industrial economy, with the mid-income level status of a region. In this phase, the use of natural resources starts to run out and waste accumulates. The last

phase is when the region reaches high income through growth with less intensity in industrialization through information and technology-driven sectors. This pivot is mainly due to regulations to protect the environment. On the EKC curve, this phase is defined after the turning point of environmental degradation is achieved (Leal and Marques 2022).

STUDIES TESTING THE VALIDITY OF THE EKC HYPOTHESIS

Existing Studies Challenging Validity

Many scholars have tested the validity of the EKC hypothesis, with studies showing mixed findings depending on the country and statistical model used. The most frequent indicator that was used as the dependent variable was CO₂ emissions for exploring the inverted U-shape relationship. Measures such as GDP, fossil fuel energy consumption, population density, and urbanization were frequently discussed together as development indicators (Işık et al. 2019; Wang et al. 2023). The references of each variable are presented in the Appendix.

Using panel data from eight OECD countries, Işık et al. (2021) found that Turkey, Australia, Canada, and France support the hypothesis in their undecomposed model, which uses regular GDP. However, when they decomposed the per capita GDP to only isolate the *increasing* section of GDP within their time-series data to more accurately test the true intended EKC relationship, none of the countries exhibited an inverted U-shape curve for the relationship between GDP and CO₂ emissions. This indicates that there are heterogeneous patterns across countries and more importantly, highlights the need for disaggregated analysis to complement longitudinal approaches and uncover hidden patterns.

A similar study was conducted to examine variations within the US by the same research team. Işık et al. (2019) analysed the EKC hypothesis across all 50 US States based on their CO₂ levels using two types of models, common correlated effects (CCE) and the augmented mean group (AMG). While the CCE approach did not find a significant EKC relationship on average, the AMG model that estimates each state individually supported the hypothesis in 14 states. Their results indicate that revealing heterogeneous effects across units enables more targeted and region-specific policy implications.

Many authors mentioned that since there are mixed findings regarding the validity of the hypothesis, more empirical studies are required to fully understand these relationships and guide future policymaking

for sustainable development. Studies that validate the relationship argue that countries validating the EKC curve have been eager to shift to adopting cleaner energy sources and governments may enforce regulations to encourage a more environmentally sustainable development strategy upon reaching a certain threshold (Apergis and Ozturk 2015; Bibi and Jamil 2021). Studies arguing the weakness of the hypothesis indicate that there may be conditions where the intensity of economic activities due to economic growth exceeds the pollution reduction enabled by innovative technologies, leading to an increase in pollution overall (Shafik and Bandyopadhyay 1992; Azomahou et al. 2006). He and Richard (2010) point to changes in industrial structure, participation in international trade, and environmental indices.

Findings From EKC Studies Based in China

China has contributed the most to the existing EKC literature (Bashir et al. 2021). Since China is experiencing a rapid growth rate and has an urgency to mitigate pollution levels, researchers have examined the relationship between economic growth and subsequent environmental degradation using various pollution indices. Like EKC studies based on other countries, while some studies validate the EKC hypothesis in China, some argue otherwise, and some reveal mixed findings due to the use of different statistical techniques and examination of diverse pollutants.

China is geographically large, and the scope of analysis varies by study. As seen in the US study above, the existence of the EKC hypothesis is likely to emerge when more disaggregated specifications with localized pollution proxies are used (Mahmoodi Nesheli et al. 2021). There are a few studies that have been conducted at the city level in China. Xie et al. (2019) corroborated the EKC hypothesis between economic growth and PM_{2.5} using spatial autoregressive models with 2015 data from 249 Chinese cities. Using both national and city-level data, He et al. (2021) found EKC heterogeneity between the western, central, and eastern regions. Their study also observed variations between cities with varying environmental regulations. Similar conclusions are drawn in Jiang and Zheng's (2017) work that explored pollution concerning income as a development index.

CONTRIBUTION OF THIS STUDY

At present, many studies around the world rely on country-level data. Since China is a large country with varying levels of socioeconomic sta-

tus across regions, a more granular investigation is warranted and our data enables this scrutiny. National panel studies have emphasized the need for spatial and temporal disaggregation, and our paper contributes to the literature by analysing the relationship between economic growth and environmental outcomes spatially at the city level through geographic weighted regressions. Estimating incorporating spatial aspects is challenging since it requires the completeness of granular data to catch their spatial effects. Currently, there are few studies incorporating spatial heterogeneity in city-level analysis within China (Gui et al. 2019; Zhao et al. 2021), but the number of studies is limited. Our study also contributes to the literature by providing an EKC validity discussion using comprehensive economic growth indicators, such as GDP and population and air pollutant measurements, including Air Quality Index, CO, and NO₂ for 151 Chinese cities. This enables understanding of characteristics of pollutants by region and informs policymakers in understanding how certain pollutants are tied to the region-specific development strategies.

Data and Methodology

DATA COLLECTION

In this study, 302 cities in mainland China were selected as the initial sample group. A total of 151 cities are included in the statistical analysis after removing cases with missing values in certain variables, mainly those related to the infrastructure-related variables. The Air Quality Index (AQI), CO, NO₂, O₃, SO₂, PM₁₀, and PM_{2.5} are used as air pollution indicators. These indicators are frequently utilized in air pollution-relevant studies (Cheng et al. 2016). The Appendix (Table A.1) presents existing studies that utilize the variables included in this study. The air pollution data are acquired from the Qingyue Data service, which is free upon request for academic research purposes (Qingyue Data 2024). The original dataset is organized by air quality detection stations, with a unique code that can be used to aggregate the data by city. All air pollution indicator data are summarized by year. The data preparation is as shown in equations (1) and (2).

$$\bar{P}_{ik} = \frac{1}{n_i} \sum_{j=1}^{n_i} P_{ijk} \quad (1)$$

$$\log P_{ik} = \ln(\bar{P}_{ik}), \quad (2)$$

where P_{ijk} is the value of air pollution indicator k at station j in city i , n_i

is the number of stations in city i , and $\log P_{ijk}$ is the log-transformed average value of air pollution indicator k in city i .

A series of socioeconomic variables are chosen based on the purpose of the study and the availability of the data. All socioeconomic data is collected by the first author from the Provincial Yearbook of Chinese Provinces in PDF versions. The yearbooks can be acquired from the local census bureau of each province.

One problem with the data used in this study is that both the air pollution data and socioeconomic data are from 2015. This is a compromise approach, given the socioeconomic data's availability and the nature of this study's objectives. This choice was necessitated by the limited availability of free air pollution data for the years 2015 and 2016, and the insufficient socioeconomic development data for major cities in 2016. The primary objective of this study is to examine the relationship between the socioeconomic development of cities and their air pollution levels, and then to assess the adequacy of the EKC in representing or explaining their relationship. The considerable variation among Chinese cities in terms of development levels, even within a single year, justifies our cross-sectional approach. Employing 2015 data does not compromise the study's validity (He et al. 2021). The absence of digitally formatted socioeconomic data for many cities in China adds to the difficulties of collecting enough valid samples.

Socioeconomic development variables include the ones representing economic scale (GDP/Capita), urbanization level (urbanization rate), industry structure (percentages of GDP generated by agriculture, manufacturing industry, and service industry), and employment structure (percent of labour in agriculture). The infrastructure established is represented by road length, electricity consumption, energy intensity, and roadway density.

One of the socioeconomic variables, the urbanization rate, is an official measurement in China based on the Hukou system (Qin and Zhang 2014). It classifies residents as either agricultural or non-agricultural based on Hukou. The urbanization rate of a city is calculated by:

$$\frac{\text{The number of residents with Non - agricultural Hukou}}{\text{Total number of residents}}. \quad (3)$$

The rates are presented in the census yearbooks. The summary of all data used is presented in Table 1.

TABLE 1 Summary of Socioeconomic Variables and Air Pollution Indicators

Category	Variable	Mean
Economic Scale	Population (*10,000)	434.13
	GDP/Capita (RMB)	51398.39
Urbanization Level	Urbanization Rate (%)	54.71
Industry Structure	% Agriculture in GDP	12.68
	% Service Industry in GDP	41.01
	% Manufacturing Industry in GDP	46.31
Employment Structure	% of labourers in Agriculture	36.54
Infrastructure	Road Length (km)	2009.63
	Electricity Consumption (10,000*kwh)	2199025.70
	Energy Intensity (kBtu/m ²)	61.73
	Roadway Density (km/km ²)	2.86
Air Pollution Indicators	Air Quality Index (AQI)	80.04
	Carbon Monoxide (CO)	1.06
	Nitrogen Dioxide (NO ₂)	30.49
	Ozone (O ₃)	59.13
	Particulate Matter ≤ 10 µm in diameter (PM ₁₀)	87.59
	Particulate Matter ≤ 2.5 µm in diameter (PM _{2.5})	49.37
	Sulfur Dioxide (SO ₂)	22.68

STATISTICAL AND SPATIAL ANALYSIS METHODS

For the statistical analysis, we designed a two-step Quadratic Regression + Spatial analysis approach.

Quadratic regression analysis

We first employed a quadratic regression model with no spatial information involved. This enables us to understand the statistical correlations between the socioeconomic variables and different air pollutants. Quadratic regression is a statistical method used to model the relationship between a dependent variable and an independent variable by fitting a quadratic equation to the data. The equation takes the form of:

$$\text{Air Pollution Indicator} = \beta_0 + \beta_1 X + \beta_2 X^2 + \varepsilon, \quad (4)$$

where X is the socioeconomic variable (e.g. GDP/Capita), β_1 is the linear coefficient, β_2 is the quadratic coefficient, and ε is the error term.

One advantage of quadratic regression is its ability to capture non-linear relationships that appear to be U-shaped or inverted U-shaped,

resembling the EKC curve. When exploring the relationship between a city's socioeconomic status and air pollution, quadratic regression allows for the examination of potential nonlinearity in the relationship. It also enables the identification of 'turning points' or thresholds in the relationship. The turning point in the EKC refers to the socioeconomic development level at which environmental degradation peaks and then starts to decline as socioeconomic development continues. The turning point is crucial for policy because, hypothetically, before the turning point, the region may focus on cleaner industrialization and proactive regulation, while after the turning point, it may accelerate environmental investment and sustainability transitions.

Mathematically, the turning point is the value of the independent variable at which the predicted air pollution indicator is at a maximum (inverted U-shape) or minimum (U-shape), depending on the sign of the quadratic term. The turning point X^* (value of X where pollution peaks) is calculated by:

$$X^* = \frac{-\beta_1}{2\beta_2}. \quad (5)$$

If $\beta_2 < 0$: the curve is an inverted U (EKC-like shape). X^* is where pollution peaks and starts declining. If $\beta_2 > 0$: the curve is a U-shape. The turning point is a minimum, not consistent with the EKC.

The turning point helps determine the socioeconomic level at which the dynamic with air pollution changes. Most importantly, quadratic regression allows quantitative measures of the relationship's direction and statistical significance, providing a more comprehensive understanding of their correlations.

Geographic Weighted Regression analysis

Following the identification of statistically significant and practically interpretable EKC-like relationships through global quadratic regression, this study employs Geographically Weighted Regression (GWR) to examine the spatial heterogeneity of these relationships. While the global model reveals overall associations across the entire dataset, it assumes spatial stationarity in the influence of socioeconomic variables on air pollution indicators. That assumption is problematic in the context of Chinese cities, where variations in industrial structure, enforcement capacity, urban form, and topography contribute to location-specific pollution dynamics. Also, the very low explanatory power of EKC shown

by quadratic regression analysis indicates the existence of uncaptured factors, which we assume are spatial factors.

GWR is selected as the spatial analysis model to account for such heterogeneity. It estimates a local regression equation at each city, weighing nearby observations more heavily than those farther away. Unlike global regression, where coefficients are fixed across space, GWR allows the regression coefficients to vary by location. This framework is particularly suited for this study, as all independent variables, such as population size, GDP, and sectoral economic shares, are continuous and numerically scaled, enabling local parameter estimates to reflect their spatial variation in explanatory power.

Technically, the GWR model can be expressed as:

$$y_i = \beta_0(u_i, v_i) + \sum_{k=1}^p \beta_k(u_i, v_i) x_{ik} + \varepsilon_i, \quad (6)$$

where y_i is the air pollution indicator in city i , x_{ik} is the value of the k -th independent variable (in this study it is the socioeconomic variables), and $\beta_k(u_i, v_i)$ are location-specific coefficients estimated at spatial coordinates (u_i, v_i) .

The estimation is done using weighted least squares:

$$\hat{\beta}(u_i, v_i) = (X^T W_i X)^{-1} X^T W_i y, \quad (7)$$

where W_i is a diagonal matrix of spatial weights determined by a kernel function. This study uses a Gaussian kernel:

$$w_{ij} = \exp\left(-\frac{d_{ij}^2}{b^2}\right), \quad (8)$$

where d_{ij} is the distance between city i and city j , and b is the bandwidth controlling the spatial extent of the local neighbourhood.

The use of GWR in this study is not intended to replace global inference but to complement it by identifying the spatial structure of variation in air pollution indicator–socioeconomic variable relationships. Doing so enables a more precise understanding of how the pairs of air pollution indicators and socioeconomic variables correlate with the spatial information considered. This approach enhances the explanatory depth of

the analysis and provides a foundation for place-sensitive environmental policy recommendations.

Quadratic Regression Analysis and Discussion

VARIABLE CHOICE

The variables are chosen based on the Pearson correlation coefficients between the natural-logged dependent variables (air pollution indicators) and the independent variables. The chosen variables are then tested with a heuristic nonlinear correlation model. We use an adaptive local linear correlation computation by segmenting the data points and applying regression tests to each segment adaptively, identifying multiple local regions of linear correlations to estimate the overall nonlinear correlation (Ranjan and Najari 2019). The correlation estimate lies between 0 and 1. The higher the value, the stronger the nonlinear correlation. Negative values are not valid here. Due to multiple local correlation computations, the net p-value of the correlation estimate is adjusted to avoid false positives. The variables that present a nonlinear relationship with the air pollutants are then used for quadratic regression analysis.

NONLINEAR ANALYSIS AND DISCUSSION

The chosen socioeconomic variables are shown in Table 2. The table demonstrates that though some of the variables might be statistically correlated with the air pollution indicators, they do not appear to have a nonlinear correlation. Socioeconomic variables are chosen for the quadratic regression test if:

1. adjusted p-value ≤ 0.01 (statistically significant correlation at the 90% confidence level),
2. nonlinear correlation estimate > 0.2 (nonlinear correlation exists).

The variables must satisfy both requirements to be eligible for quadratic regression analysis. For example, in the case of CO, the adjusted p-value supports at $> 90\%$ confidence level that population is correlated with CO, but the nonlinear correlation estimate (< 0.2) suggests that there is no nonlinear correlation between CO and population. Thus, the population is not selected for quadratic regression analysis.

O₃ is eliminated at this step because no socioeconomic variable is statistically significantly correlated with it.

Based on the results presented in Table 2, NO₂ is the pollutant that is correlated the most with the socioeconomic variables. PM₁₀ has a poten-

TABLE 2 Nonlinear Correlation Test for Statistically Significant Variables

Air Pollution Indicators	Chosen Variable	Socioeconomic Correlation Estimate (>0.2)	Adjusted p-value (<0.01)
AQI	GDP	0.107	0.05
	Population	0.208	0.01
	% Manufacturing Industry	0.109	0.06
	Energy Intensity	0.216	0.06
CO	GDP	0.246	0.81
	Population	0.095	0.1
	% Manufacturing Industry	0.181	0.01
	Road Density	0.185	0.11
NO ₂	GDP	0.455	0.002
	GDP/Capita	0.349	0.01
	Population	0.437	0.005
	Urbanization Rate	0.294	0.02
	% Manufacturing Industry	0.195	0.01
	% Service Industry	0.231	0.005
PM ₁₀	GDP	0.252	0.41
	Population	0.129	0.03
	% Manufacturing Industry	0.036	0.53
	% Employment in Agriculture	0.133	0.02
	Energy Intensity	0.201	0.08
PM _{2.5}	GDP	0.165	0.005
	Population	0.309	0.002
	% Manufacturing Industry	0.168	0.003
	Energy Intensity	0.266	0.02
SO ₂	GDP	0.249	0.101
	Population	0.028	0.63
	% Manufacturing Industry	0.167	0.002
	Road Length	0.125	0.29

tial quadratic relationship with certain variables, though none of them is statistically significant at the 90% level. Among all the socioeconomic variables, population and the percentage of manufacturing industry in GDP are correlated with the most air pollution indicators. These two variables are the ones closely related to economic and industrial activities.

Figures 1, 2, 3, 4, and 5 visualize the quadratic regression results involving the chosen socioeconomic variables and their corresponding air

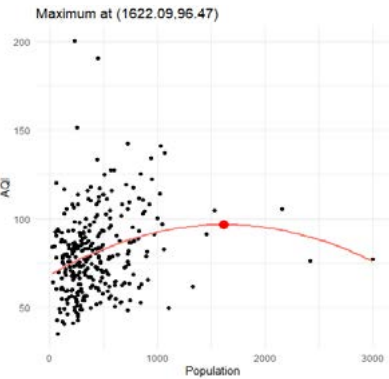


FIGURE 1 Quadratic Regression Curve for Population – AQI

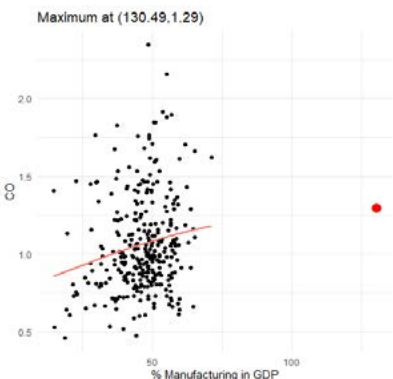


FIGURE 2 Quadratic Regression Curve for % Manufacturing Industry in GDP – CO

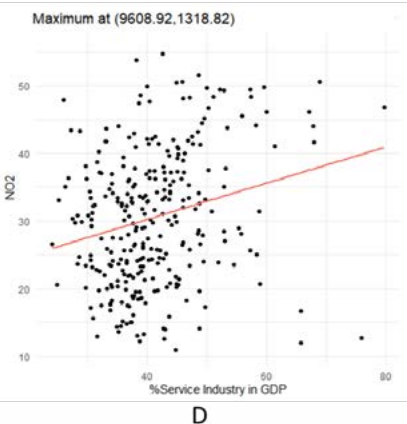
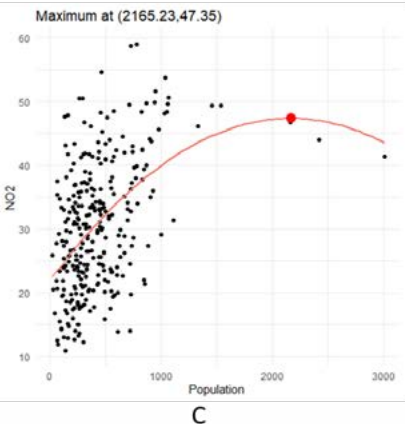
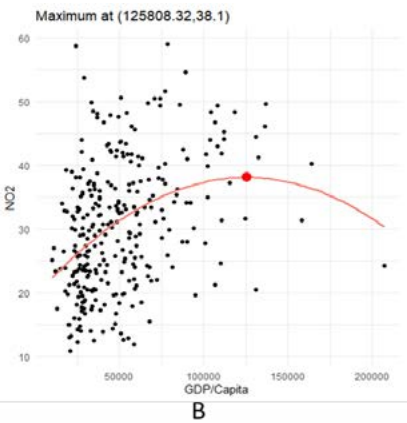
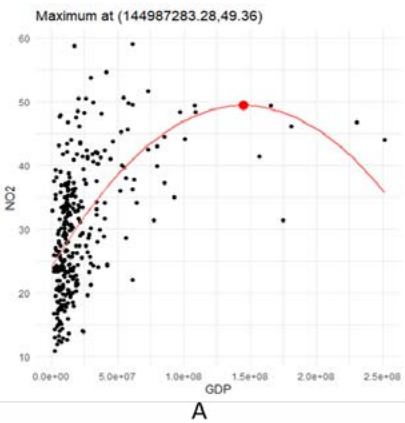


FIGURE 3 Quadratic Regression Curve for All Chosen Independent Variables – NO₂

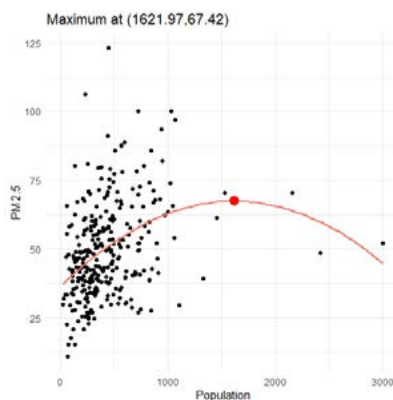


FIGURE 4 Quadratic Regression Curve for Population*10,000 – $PM_{2.5}$

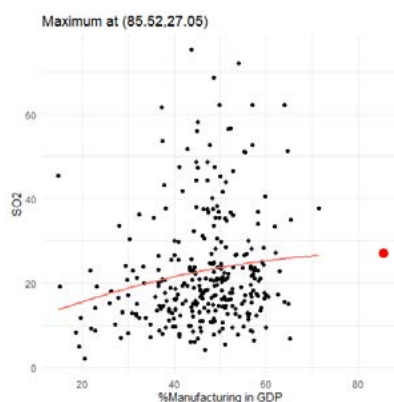


FIGURE 5 Quadratic Regression Curve for % Manufacturing Industry in GDP – SO_2

pollution indicators. Figure 3 shows that NO_2 is correlated with most socioeconomic variables that are statistically significant, showing an EKC-like pattern. The turning point occurs at 83.68% urbanization and 34.91 NO_2 concentration. This suggests that NO_2 pollution increases with urbanization but peaks around 84%. Given that some cities reach this level of urbanization, the turning point is theoretically and practically interpretable, supporting an EKC-like relationship between urbanization and NO_2 . The maximum point appears at \$125,808 GDP/capita and 38.1 NO_2 . While the EKC is statistically evident, this GDP level is extremely high and exceeds that of most cities in the dataset. This limits the practical relevance of the curve's peak.

We notice from Figures 1 and 4 that the turning points on the curves regarding the relationships between population versus AQI and $PM_{2.5}$ are very similar. This could suggest a phenomenon that, once a city reaches a more advanced economic stage with a large population, it starts to tackle air pollution issues, as the EKC hypothesis suggests.

Figure 2 shows that the maximum point of the curve representing the relationship between the percent of manufacturing in GDP and CO is (130.49, 1.29), which is meaningless in practice given the unachievable value of 130.49%. A similar pattern also appears in Figure 5, which demonstrates the correlation between the percentage of manufacturing industry in GDP and SO_2 . Figure 5 shows that the turning point on the curve is 85.52%. None of the cities have a manufacturing industry that takes over 80% of the GDP. The turning point is at 9608.92% for the per-

TABLE 3 Quadratic regression model results

Model	Intercept	Linear coeff	Quadratic coeff	Turning Point X	R ²	Adj R ²	Practi- cality	P value quad
Population_AQI	68.091	0.71	-0.0042	1622.09	0.07	0.06	Yes	0.034
%Manufacture_CO	0.733	2.95e-4	-1.17E-09	130.487	0.03	0.03	No	0.0015
GDP_NO2	23.96	3.5e-7	-1.21E-15	144987283.3	0.29	0.29	Yes	8.18e-9
GDPpC_NO2	19.526	0.0086	-3.30E-05	125808.32	0.15	0.15	Yes	0.79
Population_NO2	21.925	0.45	-0.00267	2165.23	0.22	0.22	Yes	0.62
%Service_NO2	19.422	0.27	-1.41E-05	9608.92	0.053	0.05	No	0.99
Population_PM2.5	36.252	0.03	-1.08E-05	1621.97	0.15	0.14	Yes	0.0056
%Manufacture_SO2	7.492	0.02	-5.42E-06	85.52	0.03	0.02	No	4.71e-4

cent of service industry in GDP in relation to NO₂, which is not only practically meaningless but also statistically insignificant. All these observations with practically impossible or statistically insignificant turning point values reflect a poor model fit, making the EKC concept inapplicable.

In all, among the air pollutants examined in this study, NO₂ is the most closely correlated with socioeconomic variables with an EKC-like pattern, demonstrating signs that air quality may improve as the region reaches higher stages of economic development. The quadratic regression demonstrates that the relationships of Population vs. AQI, GDP vs. NO₂, and Population vs. PM_{2.5} have statistically significant EKC-like relationships. The other air pollution indicators cannot be fully described by statistically significant socioeconomic variables in an EKC-like relationship. Table 3 presents a summary of quadratic regression results. The last column, named ‘P value quad’, is the p-value for the quadratic terms, showing whether the EKC-like relationship is statistically significant. The values in bold are statistically significant at the 90% confidence level, which will make the pairs the candidates for GWR analysis for the following step. The column named ‘practicality’ shows how practical the turning point is in reality as discussed previously.

Geographic Weighted Regression Analysis and Discussion

The original EKC hypothesis did not include consideration of spatial factors. Yet air pollutants transport and diffuse spatially. In addition, the quadratic regression analysis results indicate the presence of spatial factors of the air pollution indicators, given the very low explaining power

of the EKC hypothesis. Therefore, we disclose the spatial correlation of socioeconomic variables and air pollution indicators by GWR models by using the pairs of variables found with statistically significant EKC-like relationships in quadratic regression models. Socioeconomic variables are mapped to disclose spatial distribution in section 5.1. A Moran's I analysis result, which shows statistically significant spatial clustering patterns of air pollution indicators, is presented in Appendix Table A.2 with captions.

MAPPING THE SOCIOECONOMIC VARIABLES

China has distinctive economic subdivisions (He et al. 2002), which can be discovered in the following maps of socioeconomic variables. Figures 6 to 9 demonstrate the various development measures of 151 cities in China of GDP, urbanization rate, employment structure, and economic structure.

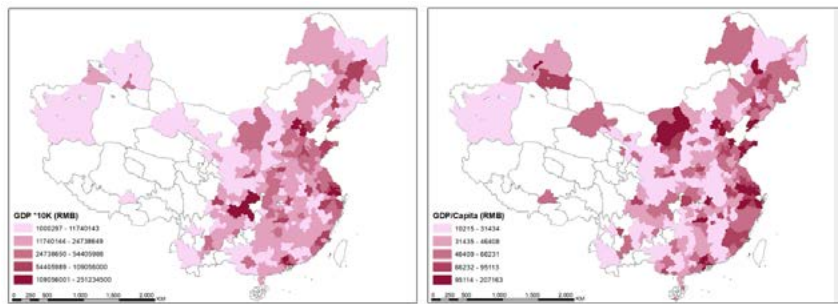


FIGURE 6 Total GDP and Per Capital GDP of 151 Cities

FIGURE 7
Urbanization Rate
of 151 Cities

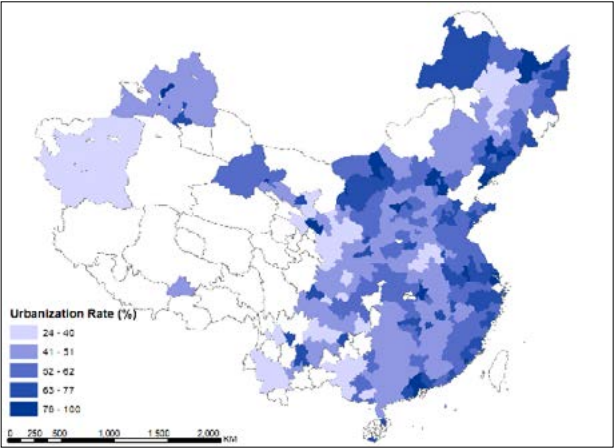


FIGURE 8
Employment
Structure
(% Employment
in Agriculture)

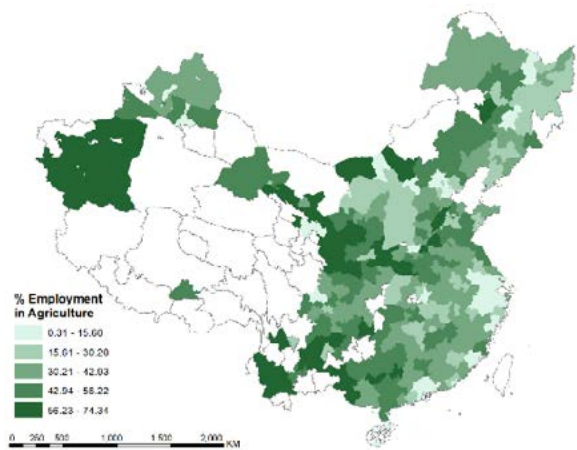


FIGURE 9
Economy Structure
(% GDP in Service
Industry)

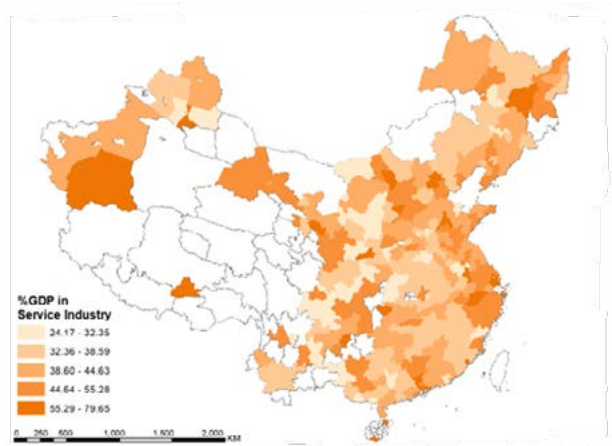


Figure 6 demonstrates that the East coastal area is the area with the highest GDP, especially the southeastern coast. This area encompasses several top metropolitan areas, including Shanghai, Guangzhou, Shenzhen, etc. The northwest and north-central areas are less developed compared to the eastern coastal areas.

Regarding urbanization rates, the northeast and east coast regions have the highest levels (Figure 7). Several central cities have high urbanization rates. This trend aligns with the spatial distribution of GDP. The employment structure (Figure 8) is represented by the percentage of employment in agriculture; the higher the ratio, the less developed the area is. The western and central areas have higher agriculture employment compared to the coastal areas and the region surrounding Beijing.

The economic structure (Figure 9) is represented by the percentage of GDP produced by the service industry. The higher this share, the lower the share of GDP produced by manufacturing and agriculture, indicating a developed city. This follows the distribution patterns of GDP and employment structure with a few exceptions, such as Hetian, a major tourist city with large ore production industries.

GEOGRAPHIC WEIGHTED REGRESSION

The first pair for GWR analysis is AQI – Population. The global linear regression model showed only a weak association, with an R^2 of 0.05 (Figure 10.C). However, residual diagnostics confirmed that model assumptions were reasonably met: the standardized residuals approximated a normal distribution with a mean near zero, and no severe heteroscedasticity was observed in the residual-versus-predicted plot.

The spatial distribution of the local GWR coefficients (Figure 10.A) reveals considerable variation in the AQI – Population relationship across cities. In eastern and central provinces (areas such as the Yangtze River Delta, Shandong Peninsula, and parts of the Beijing-Tianjin-Hebei region), GWR coefficients are strongly positive. This indicates that population concentration is associated with elevated AQI levels, likely due to compounded traffic density, construction activity, and industrial operations in these areas. In contrast, several cities in the west and far north display weak or even slightly negative coefficients, suggesting decoupling between population size and pollution levels, or just because of the lower density. The spatial variation in explanatory power is further supported by the local R^2 map (Figure 10.B). High local R^2 values (>0.6) are concentrated in the populous eastern coastal corridor and parts of the Northeast. This pattern suggests that in these regions, population size is a strong predictor of AQI variation.

Figure 11 demonstrates the GWR results of pair CO – % Manufacturing Industry of GDP. Although the global regression (Figure 11.C) suggests a limited role of manufacturing in explaining CO concentrations, the spatial analysis reveals clear clusters where the relationship is substantial. The GWR coefficient map (Figure 11.A) reveals considerable heterogeneity in how manufacturing share in GDP correlates with CO levels. Cities in the central plains (lower Yangtze River corridor), and certain inland provinces in Southwest China show positive coefficients, where higher proportions of manufacturing in GDP are associated with increased CO pollution.

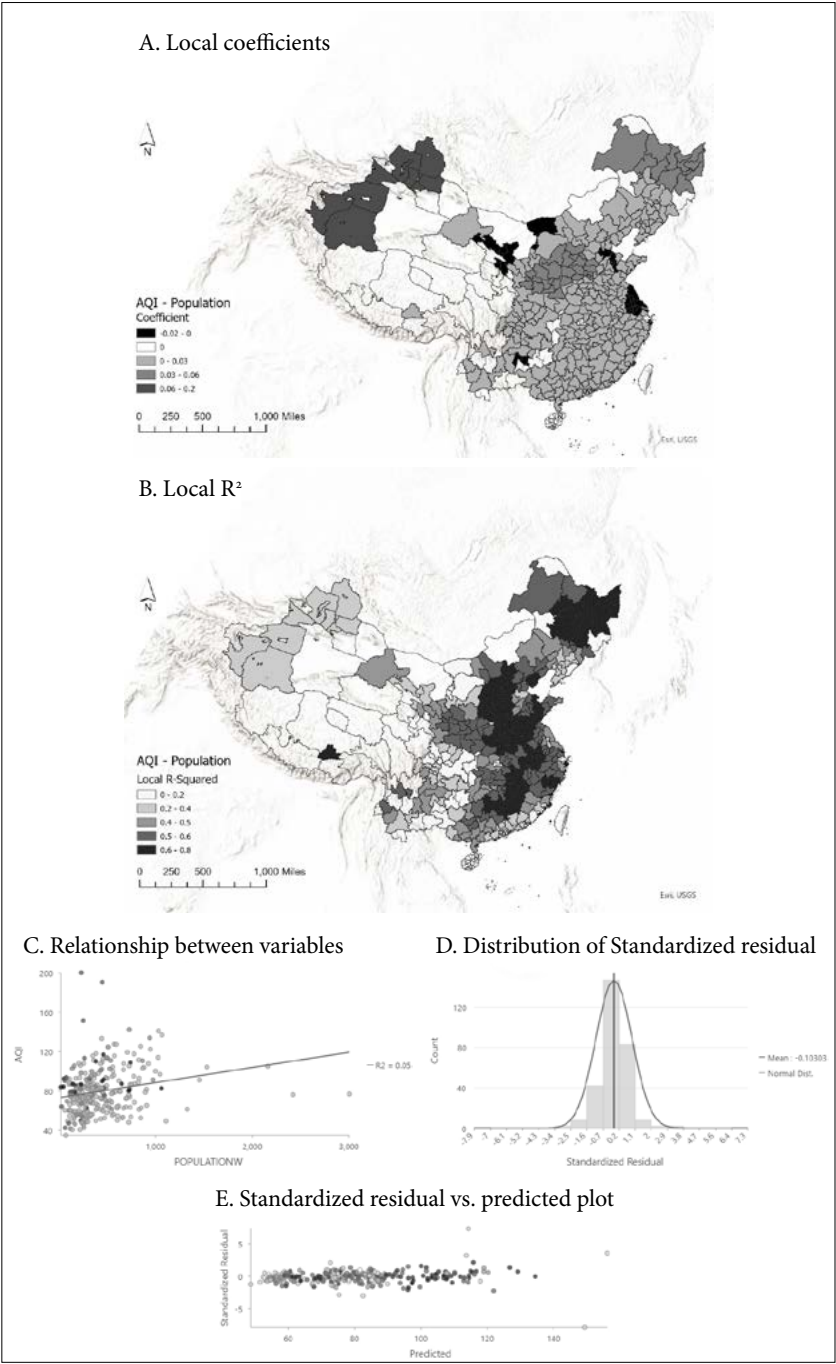


FIGURE 10 GWR results for AQI – Population

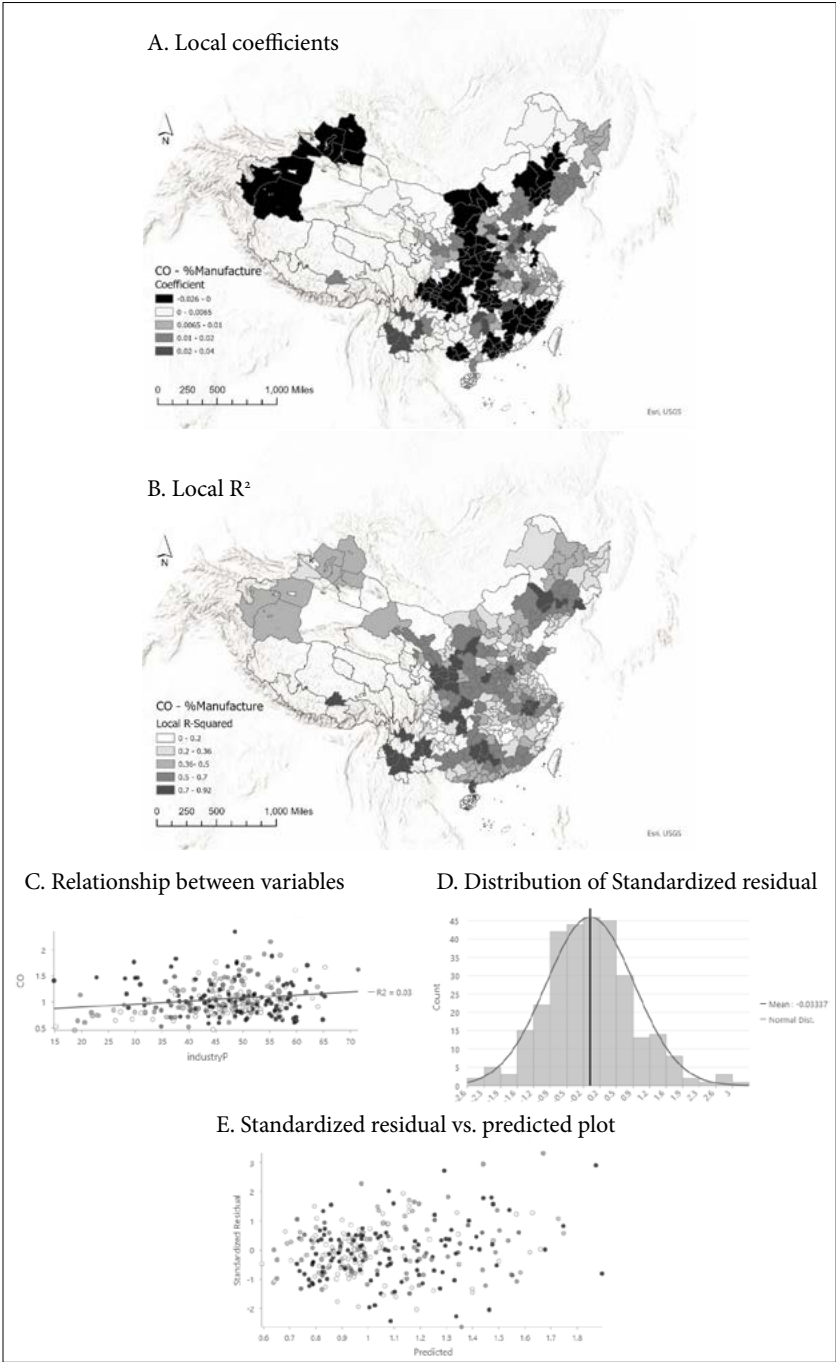


FIGURE 11 GWR results for CO – % Manufacturing Industry in GDP

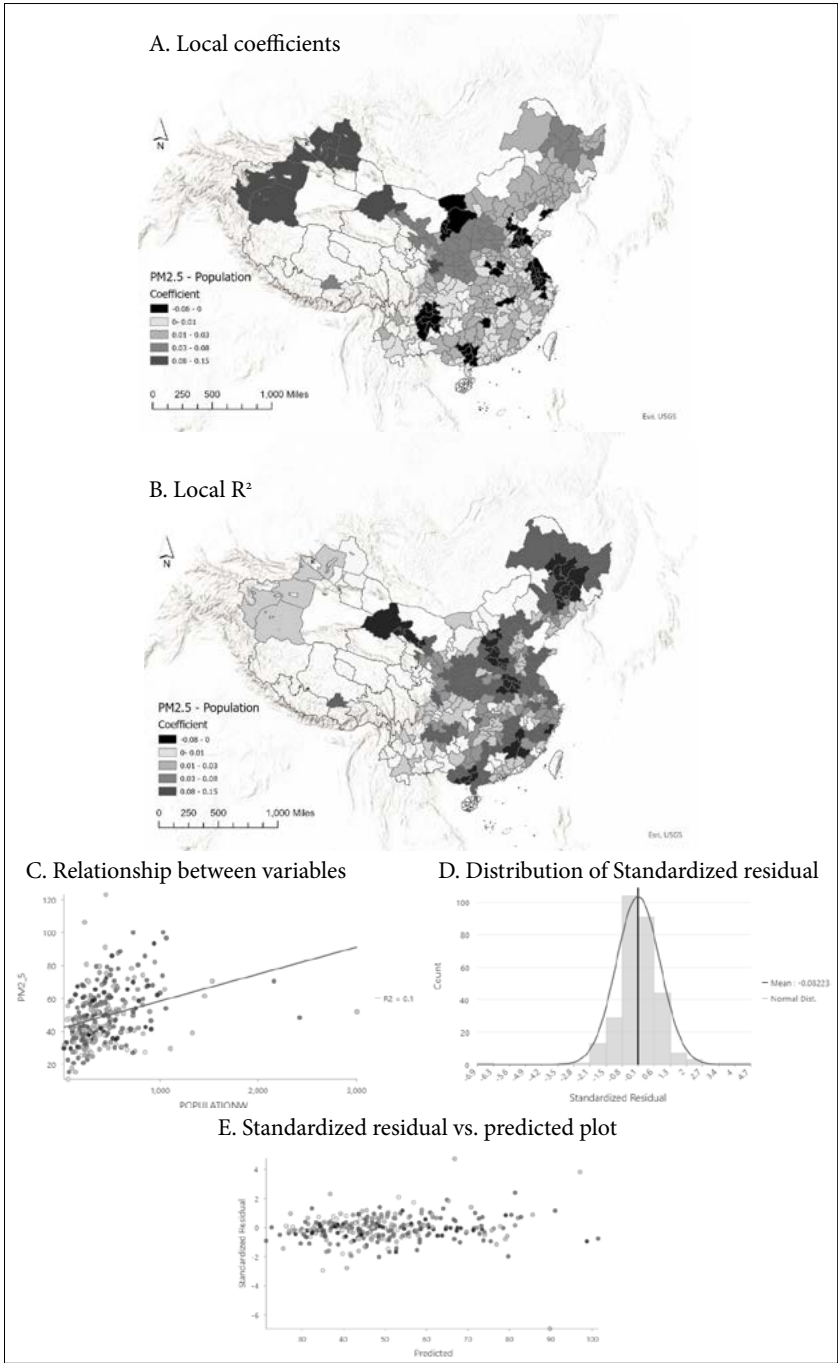


FIGURE 12 GWR results for $PM_{2.5}$ – Population

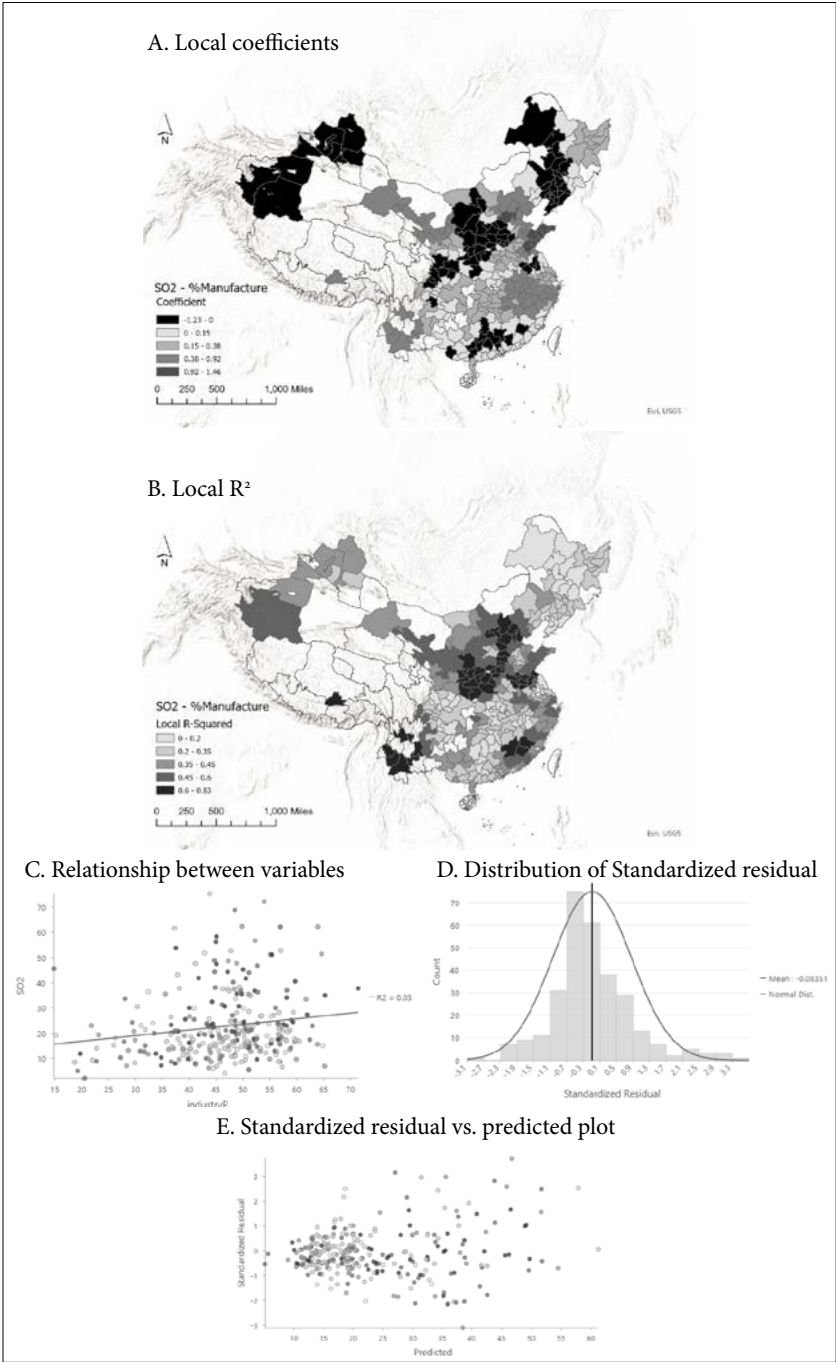


FIGURE 13 GWR results for SO₂ - %Manufacturing Industry in GDP

These areas correspond to older industrial zones and secondary cities where environmental regulation is often weaker and industrial facilities remain coal- or fuel-intensive. Conversely, in western and far northern regions including parts of Xinjiang, Inner Mongolia, and Gansu, the GWR coefficients are near zero or even negative. This may be attributed to lower population densities or non-manufacturing-dominated economies. The spatial distribution of the local R^2 values (Figure 11.B) further underscores the non-uniformity of this relationship. High explanatory power ($R^2 > 0.5$) is concentrated in the central provinces such as Henan, Hunan, and Sichuan. In these regions, the contribution of the manufacturing industry to local CO pollution is more consistent and likely reflects outdated industrial processes or higher emission intensity.

Figure 12 presents the GWR results of the pair of $PM_{2.5}$ – Population. The global linear regression results in a modest R^2 of 0.10, suggesting a limited explanatory power when assuming a constant relationship across space. Diagnostic plots indicate that model assumptions are generally satisfied. The GWR (Figure 12.A) coefficient map illustrates a strong spatial divergence in the relationship between city-level population and $PM_{2.5}$ concentrations. In the eastern coastal regions (Jiangsu, Zhejiang, and Shandong, parts of Hunan, Hubei, and Anhui), coefficients are consistently positive and exceed 0.08. These areas are highly urbanized, with dense population cores, active construction, and transportation networks. In contrast, in less industrialized or lower-density regions such as western Gansu, Xinjiang, and Inner Mongolia, GWR coefficients are negative or near zero. Cities with local R^2 values (Figure 12.B) above 0.4 cluster in the mid-Yangtze River basin and along the southeast coastal belt, where population density is most influential in predicting $PM_{2.5}$ levels. These results confirm that the relationship between population and $PM_{2.5}$ is highly spatially contingent and cannot be generalized using a single national model.

Figure 13 discloses the relationship between SO_2 concentrations and the percentage of manufacturing in GDP. The coefficient map (Figure 13.A) demonstrates that in cities across Hunan, Jiangxi, Shandong, and parts of Henan and Hebei, there is a consistently positive relationship between the proportion of manufacturing and SO_2 concentrations. These regions represent historically industrialized zones with ongoing use of sulfur-heavy energy sources, such as coal-fired power plants and outdated production processes. In these areas, manufacturing remains a

major contributor to SO_2 levels. The local R^2 map (Figure 13.B) reinforces these patterns. Stronger explanatory power clusters in the central and southern regions of China, with local $R^2 > 0.45$ in many cities. Much of the northwestern and western regions exhibit weak model fits, with local $R^2 < 0.2$, underscoring the limited relevance of this relationship in those contexts.

The spatially explicit results derived from the GWR analysis reveal meaningful heterogeneity in how socioeconomic variables correlate with air pollution indicators across Chinese cities. By moving beyond global regression models, the GWR results challenge the assumption of uniformity embedded in the traditional EKC hypothesis.

In the case of the population's influence on pollutants such as AQI and $\text{PM}_{2.5}$, the findings demonstrate phenomena traditional EKC cannot fully explain. Eastern and central coastal regions show a stronger positive relationship, even though these areas have higher socioeconomic development levels. These are likely driven by urban concentration, vehicular emissions, and energy demand, whereas less developed interior cities experience either weaker or negative correlations. Targeted interventions, such as building energy-efficient infrastructure and improving urban ventilation, must be concentrated in rapidly densifying cities where population correlates with higher pollutant levels.

Regarding industrial composition, CO and SO_2 show highly uneven associations with the manufacturing share of GDP. In industrial heartlands, particularly in parts of Northeastern Plain, manufacturing remains a substantial driver of pollutant concentrations. Yet, in cities with declining or restructured industrial sectors, the link is considerably weaker or even reversed. This reveals a critical insight for environmental governance, that decarbonization and pollution mitigation should not solely be oriented around sectoral averages, but rather spatially informed strategies that recognize which cities bear the environmental costs of national industrial output.

The localized explanatory power captured through maps of local R^2 indicates that pollution control strategies must reflect regional variations in explanatory strength. In some cases, socioeconomic factors may explain a considerable portion of pollution variance, while in others, alternative drivers, such as meteorological conditions, inter-regional spillovers, or regulatory effectiveness, may be more important. This spatial variability in model fit also exposes the limitations of EKC-inspired thinking that presumes a universal pathway from pollution to development.

Conclusion and Reflections

This study provides evidence that challenges the simplistic reliance on the EKC as a framework for environmental planning in developing regions. The quadratic regression results indicate that while certain socioeconomic indicators, such as population and GDP, show statistically significant EKC-like relationships with air pollution levels, the practicality of their turning points varies widely, suggesting that passive development alone will not lead to environmental improvement.

The GWR analysis further reinforces the limitations of a one-size-fits-all strategy. It highlights spatial heterogeneity in the strength and direction of relationships between socioeconomic factors and air pollution indicators across Chinese cities. In particular, the relationship between urban population and PM_{2.5} or AQI varies geographically, with stronger correlations found in highly urbanized regions such as the Yangtze River Delta and parts of the North China Plain. These areas require urgent, place-based strategies focusing on transit electrification, congestion pricing, and building retrofits to mitigate air quality impacts from dense urbanization.

Several limitations of this study must be acknowledged. The analysis ultimately includes 151 Chinese cities, constrained by data availability. The absence of a comprehensive digital data infrastructure at the local government level hindered access to longitudinal and standardized datasets. Our analysis is cross-sectional, relying on data from the year 2015. While this limits our ability to assess temporal dynamics, the substantial developmental heterogeneity across Chinese cities within the same year justifies a cross-sectional approach. The study eventually fulfills its central aim, to evaluate the extent to which the EKC framework can explain the relationship between urban socioeconomic development and air pollution. The findings highlight the need for caution in extrapolating EKC results and the importance of context-specific factors, including geography, data scale, and policy environments, in shaping pollution-development trajectories (He et al. 2021). Another limitation of this study lies in its omission of key confounding factors related to climate conditions, natural conditions, and the built environment in the global quadratic regression analysis. While the regression models were designed to isolate the relationship between individual socioeconomic indicators and air pollution levels, the exclusion of variables such as wind patterns, elevation, and temperature inversions may affect the robustness of the

results. However, the primary objective of the quadratic regression was to detect overarching EKC relations between economic environmental variables, not to construct fully specified atmospheric models. Their absence was therefore a necessary tradeoff to maintain model interpretability and comparability across regions. Nevertheless, their influence is not dismissed. Spatial heterogeneity captured in the GWR analysis partially accounts for such local environmental effects, reinforcing the value of a two-step approach that begins with a simplified global estimation and follows with a spatially adaptive local model. Future studies incorporating climate and physical geography layers could enhance the explanatory power and realism of pollution modelling in urban settings.

When planning future strategies for air pollution mitigation, policymakers in developing countries should be cautious in relying on the EKC as a guiding framework. The air pollution policy should be geographically and economically sensitive. In industrial regions where manufacturing remains strongly linked to CO and SO₂ emissions, as evidenced by elevated local coefficients and R² values, regulatory attention must be directed toward industrial upgrading. This includes retrofitting facilities with low-emission technologies, enforcing stricter emissions caps, and incentivizing the relocation or transformation of high-polluting industries into greener sectors. However, unlike historical patterns in developed countries, simply shifting pollution-intensive industries to less developed regions is no longer a viable or ethical strategy. The focus must shift toward real mitigation rather than spatial displacement. And recent studies even suggest that including renewable energy variables may improve the explanatory power of EKC models in the Chinese context (Chen et al. 2019; Dong et al. 2019).

Uneven GWR explanatory power suggests the presence of alternative drivers of pollution, such as atmospheric transport, externalities from neighbouring cities, or uneven enforcement of environmental policy. These cases point to the need for improved regional coordination and air quality management at broader spatial scales. Inter-jurisdictional mechanisms such as regional emissions trading schemes, shared air monitoring networks, and cross-boundary pollution control agreements may be necessary to address these systemic spillover effects.

Furthermore, the limitation of this study reveals the importance of integrated data systems for supporting differentiated policy design. Many of the limitations in this study, particularly the inability to conduct longitudinal analyses, stem from the lack of consistent city-scale data at the

national level. Building transparent, interoperable, and regularly updated data infrastructures will not only improve future research but also strengthen cities' capacity to design policies responsive to their unique environmental challenges.

In all, policymakers should abandon overreliance on theoretical EKC trajectories and instead adopt differentiated strategies grounded in empirical relationships observed at the city level. Pollution control interventions must be locally tailored, technologically adaptive, and regionally coordinated to reflect the spatial complexity of socioeconomic-environmental interactions in contemporary urban China. Efforts to reduce pollution must be deliberate, not deferred. Policy should focus on reducing emissions at the source rather than displacing pollution geographically or temporally. Relying on passive structural shifts, such as sectoral changes or deindustrialization, is unlikely to yield equitable or sustainable outcomes without targeted environmental regulation, investment in clean technologies, and regional coordination.

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Appendix

TABLE A.1 References for variables used in this study

Type	Variable	References
Socioeconomic variables	GDP/Capita	Işik, Ongan, and Özdemir (2019); Nasrollahi et al. (2020)
	Urbanization rate	Bashir et al. (2021)
	Population	Işik, Ongan, and Özdemir (2019); Nasrollahi et al. (2020)
	Road length	Wang and Zha (2024)
	Energy intensity	Bashir et al. (2021); Nasrollahi et al. (2020)
	% Service Industry(S) in GDP	Li et al. (2019); Nasrollahi et al. (2020)
	% Manufacturing Industry in GDP	Li et al. (2019); Nasrollahi et al. (2020)
	% Labourers in Agriculture	Li et al. (2019)

TABLE 2 Continued

Type	Variable	References
Air pollution variables	Air Quality Index	Wu et al. (2018)
	CO	Dasgupta et al. (2002); Nasrollahi et al. (2020)
	NO ₂	Dasgupta et al. (2002)
	PM ₁₀	Dasgupta et al. (2002); Krzyzanowski et al. (2014)
	PM _{2.5}	Dasgupta et al. (2002); Krzyzanowski et al. (2014)
	SO ₂	Dasgupta et al. (2002)

TABLE A.2 Morans' I analysis results of air pollution indicators

Air Pollution Indicator	Moran's I Index	Z-score
AQI	0.2249	44.8032
CO	0.1552	31.0061
NO ₂	0.1682	33.4775
PM _{2.5}	0.2122	42.1551
PM ₁₀	0.1702	34.6849
SO ₂	0.2045	40.7122
O ₃	0.0735	15.1473

Overall, Moran's I results show that all air pollution indicators tend to spatially cluster. Table A.2 shows the Moran's I analysis results. While Moran's I index is not very high, all values are close to each other, suggesting that the difference between clusters is not very large. Also, the Index shows that AQI, PM_{2.5}, and SO₂ have the most evident clustering pattern. Moran's I values range from 0.0735 (for O₃ - Ozone) to 0.2249 (for AQI), with Z-scores well above the conventional threshold for statistical significance (e.g., $Z > 2.58$ at $\alpha = 0.01$). These results suggest that, while the spatial patterns of air pollution are not random, the degree of spatial dependence is generally weak to moderate across the study area.

Moran's I results show that there is a clear tendency for cities adjacent to exhibit similar air quality. The results suggest that the EKC, when applied without accounting for spatial interactions, risks misrepresenting the true dynamics of pollution change. Spillover effects disrupt the closed-system logic of the EKC, calling for more spatially informed models and multi-scalar policy responses that reflect the interconnected nature of urban environmental systems. Further, this indicates that the smaller cities could potentially suffer from the air pollution produced by neighbouring metro areas and thus must bear the environmental cost caused by the large cities' activities. Therefore, based on the findings, especially for the air pollution indicators that show strong clustering patterns, such as AQI, PM_{2.5}, and

SO₂, the EKC curve may not be directly applicable for measuring the relationship between economic development and air quality.

The relatively low Moran's I values can be attributed to several practical and methodological factors. First, air pollution tends to originate from highly localized sources, such as traffic corridors, industrial zones, and specific land uses, which do not always align with broader regional spatial trends. Second, the heterogeneity among urban systems in terms of industrial structure, population density, topography, and infrastructure introduces considerable spatial noise, further weakening the degree of measurable spatial autocorrelation.

Despite the low magnitude of the Moran's I indices, their associated Z-scores indicate a high degree of statistical significance. This implies that the observed spatial clustering, though limited in strength, is not a product of random spatial arrangement. These findings emphasize the importance of localized environmental management strategies. Furthermore, the results support the validity of employing non-spatial regression models in this study, complemented by spatial diagnostics, rather than fully spatial econometric models that assume strong spatial dependence in the dependent variable.

Moran's I results offer critical insight into the limitations of the EKC, particularly in its assumption that the relationship between economic development and environmental degradation is spatially self-contained. While the EKC hypothesis assumes that pollution levels will rise and eventually fall as a region develops economically, it implicitly assumes that environmental outcomes are primarily determined by internal economic dynamics, rather than by interactions with neighbouring regions.