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Investigating Spatial Heterogeneity of the Environmental Kuznets Curve for Haze Pollution in China

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Abstract: This study investigates the environmental Kuznets curve (EKC) for haze in 31 cities and provinces across China using the spatial data for a period of 15 years, from 2000 to 2014. We utilized the geographically weighted regression (GWR) model to consider the spatial non-stationary characteristics of the air quality in a vast territory. This approach allowed us to verify the region-specific characteristics, while the global model estimated the average relationship across the entire nation. Although the EKC for haze was statistically significant in the global models, the results only confirmed the existence of an EKC between the overall air quality and economic performance. Thus, it was difficult to determine the regional differences in an EKC. The results of the GWR model found the spatial variability of each variable and showed significant spatial heterogeneity in the EKC across regions. Although six regions—Beijing, Gansu, Heilongjiang, Jiangxi, Jilin, Liaoning, Shanghai, Tianjin, Xinjiang, and Zhejiang—showed inverted U-shaped EKCs, these were only statistically significant in three big cities—Beijing, Tianjin, and Shanghai. The results demonstrated no EKCs in the other 25 provinces and cities. These results provide strong empirical evidence that there is significant spatial heterogeneity in the EKC of China. Thus, a more regionally specialized air pollution control policy is required to create an effective policy for balanced economic growth in China.

Keywords: China; environmental Kuznets curve; geographically weighted regression; haze; spatial heterogeneity

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1. Introduction

China has emerged as one of the largest and most robust economies in the world. The ruling Chinese Communist Party made the decision to open up the country for trade and investment, as well as adopting a limited number of capitalist strategies. This is a natural progression toward a better model for regional trade and local growth [1]; however, regional discrepancies in sustainable development in China are among the barriers to future success [2].

The rapid industrialization in China has caused side effects, with the leading issue being environmental challenges. Currently, the most prominent environmental issue is air pollution. The haze phenomenon has significantly and negatively affected economic performance and contributes to environmental pollution in China. Haze is defined as the introduction of particulate matter (PM), biological molecules, and other contaminants into the atmosphere. The presence of excess suspended matter in the atmosphere can disrupt the daily life of humans. These contaminants usually negatively affect the health of humans and other living organisms. Furthermore, they damage crops, natural environments, and built environments [3,4]. It can also affect the economic performance of a region by causing declining employee performance, haze-related illnesses, slower crop growth, low visibility, and other issues [4].

In recent years, large cities in China have frequently experienced severe fog and haze episodes that disrupt visibility. There have been rapid changes in the patterns of haze and fog occurrence in these areas over the past several decades. For example, in research about the occurrence of haze and fog in the North China Plain, the occurrence of haze and fog was quite low from the 1950s to the 1980s but reached a peak from 1981 to 1998 [4,5]. Since 2000, haze pollution has shown a rapid increase; one of the reasons for this is that China's policy of opening up stimulates the evolution of industries. The haze problem became more noticeable in the mid-2000s, when environmentalists observed that the haze was not associated with the changing of the seasons. Instead, these particles remained in the air perpetually. In 2013, the Chinese Academy of Sciences documented the occurrence of a severe episode of haze, which affected northern and eastern China.

One of the most affected places was Beijing, which is the administrative, economic, and cultural center of China, meaning that the negative effects there far outweighed those in other regions. Beijing's high population density means that the people affected outnumber those affected anywhere else in the country. In Beijing, air pollution index (API) values of 900 have been recorded, making the environment toxic to its local residents (an API of 0–50 is considered good, 50–100 is moderate, 101–200 is unhealthy, 201–300 is very unhealthy, and anything above 300 is classified as hazardous). In terms of economic losses, Beijing lost approximately 254 million USD, which was about 0.008% of the total gross domestic product (GDP) of Beijing in 2013 [6]. Previous studies have examined the effects of haze on China's economy and most found that haze reduces economic performance as well as human resources [7–10].

Previous studies have tried to investigate the existence of an environmental Kuznets curve (EKC) in China to show the relationship between economic development and environmental performance and understand the current pollution status [11–19]. Scholars have analyzed the EKC for haze using data regarding the concentrations of PM, carbon dioxide (CO_2), sulfur dioxide (SO_2), and nitrous oxide in the atmosphere [20–23]. (PM is classified into different sizes, the most commonly measured of which are PM_{10} and $PM_{2.5}$. There has been a significant debate between researchers as to which is the better measurement system, but measuring $PM_{2.5}$ appears to be the preferred method in China as it has been found to be the dominant polluting agent). To investigate the heterogeneity of the EKC across regions in China, some studies have considered the spatial differences in the EKC and found significant spatial heterogeneity [16,20–25]. However, most studies focused on a certain pollutant, such as SO_2 or PM; thus, it was difficult to discover the EKC between overall air quality and economic performance.

Scholars have also attempted to identify the determinants of haze [7–10,26,27]. The energy structure is one of the crucial factors affecting haze. Scholars have suggested that the heavy usage of coal, renewable energy, and energy consumption have an influence on haze; however, the empirical evidence is still controversial [27–29]. Other socio-economic factors, such as income, human capital, trade openness, transportation, and population density, have also been considered as determinants of haze [16–19]. Moreover, if we widen the perspective, we should not overlook the impact of meteorology and stable atmospheric conditions on atmospheric pollution. For example, the amount of rainfall and temperature have been regarded as factors that influence the haze problem [25].

This study seeks to determine which economic factors influence haze and which regions have an EKC and turning point. Considering the spatial heterogeneity of economic growth and the haze phenomenon, this study applies the geographically weighted regression (GWR) model to investigate the EKC between haze and economic determinants for 31 Chinese cities. The overall air-quality data API and factors including the gross regional product (GRP), trade openness, and population density are used for analysis. After determining that the EKC has an inverted U, we verify and calculate the turning point, i.e., the decline in pollutants in line with increased economic performance [30]. The results from the GWR approach, which is suitable for considering the spatial non-stationary characteristics in vast territories, can provide a better understanding of the spatial heterogeneity of the haze problem in provinces in China with visual evidence. Moreover, the estimation of the turning points of the EKCs using the GWR estimations can be used to identify trends in sustainable development after the analysis periods. Through these processes, this study determines whether any stronger measures should be undertaken by the Chinese government to curb the haze issue, as it may affect the livelihood of the nation.

2. Materials and Methods

In this study, we utilized an EKC model to study the haze in China using a database of 31 cities and provinces across China from the period 2000 to 2014. To verify whether there was a significant difference in the regional economic capacity or innovation ability during the same period, we first applied global regression models to grasp the overall EKC of the entire country. We adopted the EKC model, as modified by Kang et al., to study the relationships among CO_2 emissions in China [31]. Interestingly, this study adopted the API, which is an overall measure of pollution that encompasses particles of all sizes, to determine the level of haze for each region, unlike previous studies, which used data regarding each pollutant. The API has been recommended as a sustainable indicator in air-quality assessment since it can overcome difficulties in interpretation of research results and problems of subjective classification of air quality [32].

In addition to the EKC analysis of haze in the form of API readings, we included the possible determinants of the environmental elements of haze—per capita GRP, trade openness, and population density—-in the analysis. To verify the inverted U shape, per capita GRP and its square were included in the model. Trade openness represents the degree of economic openness, which reflects economic competitiveness and the flow of goods and services. Previous research insisted that the opening up of the economy by the Chinese government affected the degree of pollution [33]. This study also considers population density as the indirect measure of active economic activities [25]. Data regarding the GRP, trade openness, and population density were taken from the China Compendium of Statistics for the period 2000–2014 and the China Statistical Yearbook [34]. The API levels for all 31 cities in China were obtained from China's Environmental Agency.

The EKC model used in this study is given as follows:

$$\ln(Y_{it}) = \alpha_{it} + \beta_1 \ln(\mathrm{PGRP}_{it}) + \beta_2 \ln(\mathrm{PGRP}_{it})^2 + \beta_3 \ln(\mathrm{TR}_{it}) + \beta_4 \ln(\mathrm{PD}_{it}) + \varepsilon_{it} \quad (1)$$

where Y_{it} is the haze level measured in API per capita, PGRP stands for per capita GRP, TR is the trade openness expressed as ratio of the gross export and import value to the GRP, and PD represents the population density in each of the 31 cities in China. i and t represent the region- and time-specific data.

The following models can be utilized for analysis to consider autocorrelation within panels and cross-sectional correlation and heteroskedasticity across panels: the pooled ordinary least squares (OLS) model, the fixed- and random-effects models, and the generalized least squares (GLS) model. This is because there can be subtle or no changes in a geographical area over time, which can cause homogeneity in the parameters of each spatial unit. An F-test, a Breush–Pagan Lagrange multiplier (LM) test, and a Hausman diagnostic test were conducted to determine which model provided the best fit for the data. Pesaran's test was also conducted to determine cross-sectional dependence.

Next, considering the spatial heterogeneity of each city and province, we performed a local linear regression using the GWR model. The GWR model has been used in earlier studies, such as in the Hedonic Pricing Model. The GWR model is also known as the local model and shows regression coefficients that vary across space, showing the spatial variations and relationships between the environmental determinants and their environmental factors via a local estimation done. The results allow us to understand how the regional determinants at a provincial level affect EKCs [2,21].

According to Wheeler [35], the GWR model is based on the linear regression model and assumes that the regression coefficient is a function of the observation point location. The GWR model focuses on the local geography, making it locally weighted. Thus, its performance from the perspective of spatial econometrics can be illustrated by using spatial heterogeneity. For the GWR model, we followed Fotheringham et al.'s approach [36] to consider regions expressed differently from the global models. This model expands the global model as follows:

$$Y_i = \beta_0(u_i, v_i) + \sum \beta_k(u_i, v_i) X_{ik} + \varepsilon_i \tag{2}$$

where Y_i and X_{ik} are the dependent and independent variables, respectively. (u_i, v_i) represents the location i of the observation and ε_i is the error term. The estimation for the GWR model is given as follows:

$$\beta' = \left[X^T W(u_i, v_i) X\right]^{-1} X^T W(u_i, v_i) Y. \tag{3}$$

where $W(u_i, v_i)$ is the square matrix of the weight assigned to a location (u_i, v_i). X and Y are the geographically weighted matrices of the values of the independent and dependent variables. The matrix of the geographical weights, $W(u_i, v_i)$, is as follows:

$$W(u_i, v_i) = \begin{bmatrix} W_1(u_1, v_1) & 0 & 0 \\ 0 & \cdots & 0 \\ 0 & 0 & W_n(u_1, v_1) \end{bmatrix} \tag{4}$$

The GWR model estimates the coefficients for each region, assuming that a closer observation has a greater effect on the parameters than a more distant observation. Based on the equations above, the specific model for the EKC can be expressed as follows:

$$Y_{it} = \alpha_{it} + \beta_1(u_i, v_i) \ln(\mathrm{PGRP}_{it}) + \beta_2(u_i, v_i) \ln(\mathrm{PGRP}_{it})^2 + \beta_3(u_i, v_i) \ln(\mathrm{TR}_{it}) + \beta_4(u_i, v_i) \ln(\mathrm{PD}_{it}) + \varepsilon_{it} \tag{5}$$

where Y_{it} is the per capita volume of the API in province or city i for the year t. (u_i, v_i) denotes the location i's longitude and latitude coordinates. PGRP and PGRPSQ denote the provincial gross regional product per capita and its squared term. TR is the trade openness expressed as the ratio of gross export and import value to the GRP. PD is population density (in people/m^2). This study utilized STATA for the global models, GWR 4 software for the spatial models, and QGIS for the mapping process. Table 1 presents the descriptive statistics.

Table 1. Descriptive Statistics of Variables.

Variable	Unit	Obs.	Mean	Median	Maximum	Minimum	Std. Dev.
API	Index	465	294.518	307.000	365.000	168.000	48.783
PGRP	100 million CNY	465	25,076.280	19,580.230	103,671.300	2742.070	19,679.650
TR	%	465	13.929	3.600	100.220	0.001	22.425
PD	Person/m^2	465	414.479	263.000	4349.000	2.000	621.088

Note: The data observations for each region for 15 years are consistent with the calculation of 15 years multiplied by 31 regions, which equals 465.

The determinant with the largest standard deviation is the PGRP, which indicates how varied the per capita income is for different regions in China. This is also seen in the trade openness variable, where some regions have almost no trade whatsoever and other regions trade almost all of their products. There is also a surprisingly significant difference in the population density across the regions, which can be attributed to the fact that China has a large land area and some places have a more inhospitable topography, which makes it difficult to farm and earn a living. Most of China's population is concentrated along coastal cities, with lower population density further inland.

3. Results

3.1. Subsection Results of Global Models

In this study, first, we tested the global models using the EKC formulas to understand the determinants of haze. Table 2 shows the results of the global models and the verifications of their fitness. The results demonstrate that the F-test value rejects the null hypothesis with a value of 210.19 with high statistical significance, and the Breush–Pagan LM test value also rejects the null hypothesis with a value of 2727.87 with a p-value of 0.000. Thus, both the fixed- and the random-effects model showed a better fit than the simple OLS model. However, the results of the Pesaran's test for the cross-sectional dependence show cross-sectional dependence in the models. In this regard, this study applied the GLS model to consider the autocorrelation within panels, cross-sectional correlation, and heteroskedasticity across panels.

Table 2. Estimation Results of Global Models.

Variable	Pool OLS	FE	RE	GLS
Intercept	5.518 *** (1.167)	6.356 *** (0.539)	5.938 *** (0.376)	5.675 *** (0.165)
$\ln(PGRP_{it})$	0.156 (0.236)	−0.008 (0.078)	0.032 (0.069)	0.122 *** (0.034)
$\ln(PGRP_{it})^2$	−0.013 (0.007094)	−0.003 (0.004)	−0.005 (0.004)	−0.011 *** (0.002)
$\ln(TR_{it})$	0.014 * (0.007)	0.001 (0.004)	0.001 (0.004)	0.013 *** (0.001)
$\ln(PD_{it})$	−0.012 (0.009)	−0.059 (0.046)	−0.013 (0.019)	−0.011 *** (0.001)
R^2	0.168	0.090	0.150	
F-test/Breush–Pagan LM test		210.19 ***	2727.87 ***	
Pesaran's test		4.041 ***	4.948 ***	

Note: ***, and * indicate significance at the 1% and 10% levels, respectively.

The results from the GLS model confirm the existence of an EKC in overall cities and provinces across China for the period 2000–2014. The PGRP variable shows a positive coefficient of 0.122, while the PGRP square's coefficient is negative, and both variables are statistically significant. These results indicate that significant EKCs have inverted U-shapes. Moreover, the positive value of the PGDP coefficient indicates that production activities contribute to haze concentrations; this finding supports those of previous studies, which suggested that production activities are the main contributors to haze concentrations [25,37]. This result shows the necessity of balanced environmental regulation, even if China's internal policy still prioritizes economic growth.

The trade openness has a positive coefficient at the 1% confidence level. The empirical evidence reveals that increasing trade openness results in an increase in API across China. This result is in line with previous research, which found a negative impact of the opening-up policy in China on haze pollution [33]. The population density variable has a negative coefficient at the 1% confidence level. The population density result shows that increases in population density cause a drop in API. This was an unexpected result, since population density is one of the indirect measures of active economic activity, which contributes to the increase in industrial emissions, including the haze phenomenon [25].

Even though the GLM model found the existence of the EKC for haze pollution, the global model only confirmed the existence of an EKC between overall air quality and economic performance in China. Thus, it is difficult to grasp the regional differences in the EKC [2,21,25]. Considering the possibility of significant spatial heterogeneity in the economic status of regions in China, it is necessary to investigate the heterogeneity of the EKC for each region.

3.2. Results of Geographical Weighted Regression Models

To verify the necessity of the spatial approach, we tested the spatial variability. Table 3 presents the results of the test for the spatial variability of the GWR coefficients. The differential criterion values are negative and highly significant, meaning that the variance of the regression values across the different provinces in China are also extremely high. These results demonstrate that there is significant spatial variability in terms of the model's selection criteria.

Table 3. Spatial Variability Test.

Variable	F	Diff of Criterion
Intercept	68,192.880 ***	−3960.470
$\ln(PGRP_{it})$	250.132 ***	−1049.020
$\ln(PGRP_{it})^2$	1473.370 ***	−1915.418
$\ln(TR_{it})$	54.240 ***	−379.452
$\ln(PD_{it})$	1516.960 ***	−1548.354

Note: Positive value of diff-criterion indicates that there is no spatial variability in terms of model selection criteria. *** indicates significance at the 1% level.

The spatial variability test results provide strong evidence that the EKCs are not always constant but, instead, vary among provinces or cities in China. The main contributors to the $PM_{2.5}$ in haze are coal and fossil-fuel burning, especially from vehicles and energy-intensive industries, and they are thus likely to be linked to the different levels of economic activity in a certain city [38]. However, the previous global OLS models could not capture these spatial differences, since the global model estimates the average relationships among all the provinces or cities in China to be in line with the findings of previous studies [21,25].

Table 4 presents the estimation results of the GWR model. The GWR parameter estimates for the independent variables show the distribution of the coefficients across regions that vary widely over space. The Akaike information criterion (AIC) value of the GWR model is also lower, at −1461.025, than the OLS value, of −324.234. Thus, the GWR model is superior to the global model.

Table 4. Estimation Results of GWR Model.

Variable	Min	LQ	Med	UQ	Max
Intercept	0.196	4.240	7.348	9.667	16.167
$\ln(PGRP_{it})$	−1.585	−0.726	−0.206	0.443	1.120
$\ln(PGRP_{it})^2$	−0.053	−0.026	0.008	0.032	0.079
$\ln(TR_{it})$	0.031	−1.099	−0.074	0.013	0.622
$\ln(PD_{it})$	−1.099	−0.325	0.016	0.047	0.147
N			465		
Adjusted R^2			0.939		
AIC			−1461.025		

The GWR model results confirm the spatial variability and indicate that there is significant spatial heterogeneity in the EKCs. In this regard, we investigated the existence of the EKC between the economic performance and the haze using the local coefficients from the GWR model for each of the 31 regions. One of the advantages of the GWR model is that the estimated results are spatially displayed, based on the resolution of the data used in the study. Since, in this this study, we conducted province- or city-level local regression, it is possible to display all the results using a provincial or municipal map of China generated by QGIS. Figure 1 presents the illustrated spatial variations in the EKC for haze in China.

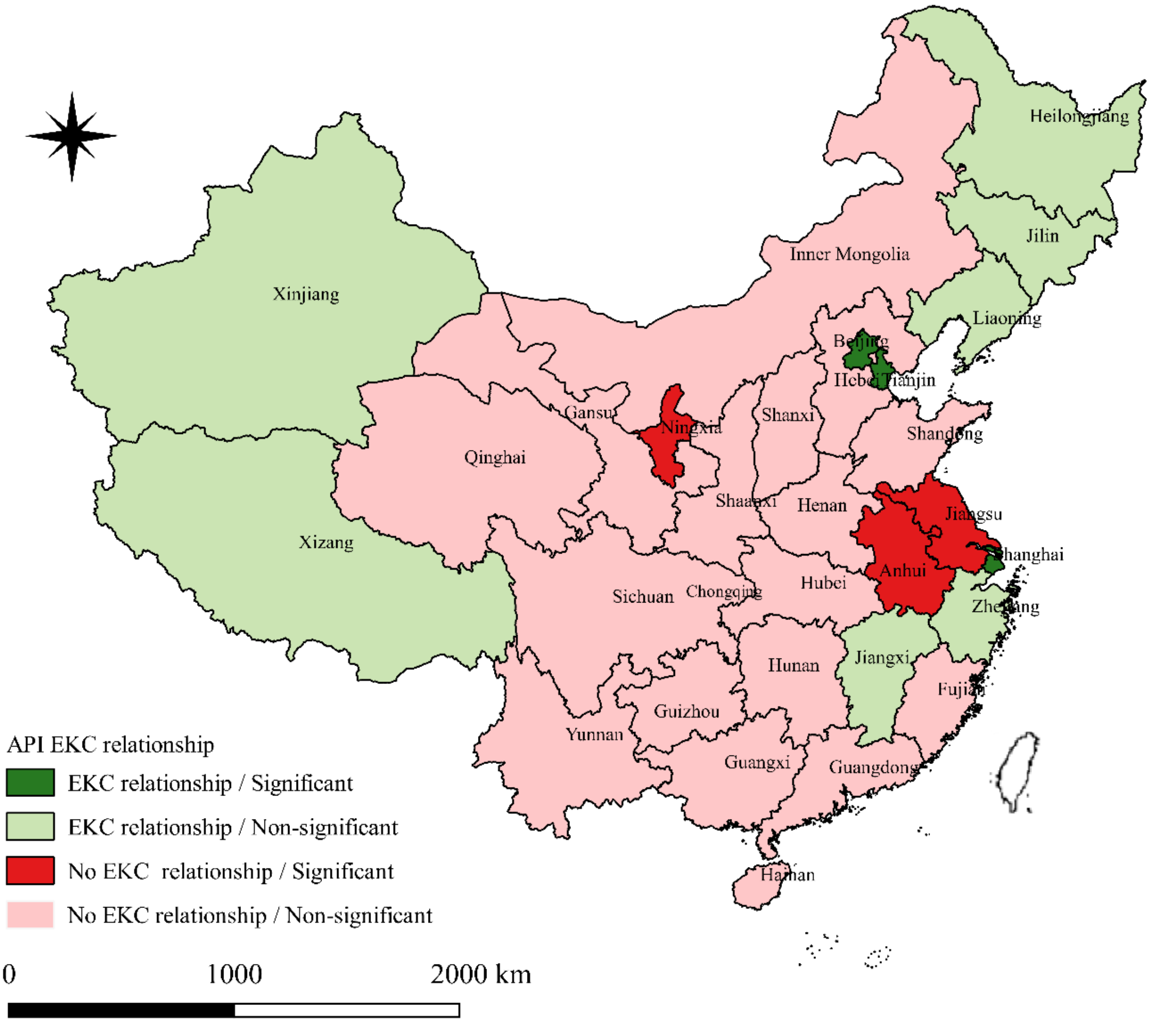

Figure 1. EKC for the haze in China.

Figure 1 shows the significant spatial heterogeneity of the EKC for haze in China. We colored the regions based on the significance and shape of their EKC (i.e., the symbols β_1 and β_2 in Equation (5)), which was calculated by the GWR estimation results. We verified the EKCs based on the sign and significance of the coefficients of the PGRP and the squared term of the PGRP variables. There were four cases based on the statistical significance and sign of the coefficients. Specifically, if the coefficient of β_1 had a plus sign and that of β_2 had a minus sign, the EKC had an inverted U-shape. Moreover, if β_1 and β_2 were statistically significant, it was possible to confirm the existence of EKCs in certain regions.

Six regions—Beijing, Gansu, Heilongjiang, Jiangxi, Jilin, Liaoning, Shanghai, Tianjin, Xinjiang, and Zhejiang—show inverted U-shaped EKCs. However, only three big cities (dark green colored regions in Figure 1)—Beijing, Tianjin, and Shanghai—show a statistically significant inverted U-shape between air quality and economic performance. According to the results, there are no EKCs in the other 25 provinces and cities, and only three regions—Anhui, Jiangsu, and Ningxia—are statistically significant. These findings support the necessity of balanced environmental regulation, even if China's internal policy still prioritizes economic growth. When considering these spatial analysis results, it is important to note that the initial control policies are currently working in certain big cities, such as, Beijing, Shanghai, and Tianjin, albeit to a lesser degree of effectiveness. However, it is necessary to perform a long-term analysis of the EKCs for haze, especially in statistically non-significant regions.

3.3. Estimation of the Turning Points of the EKCs for Haze

Based on the empirical results from the GWR analyses, it was possible to calculate the turning points of the EKCs for the haze in China. We used local coefficients of the three regions that showed a significant EKC for haze. Table 5 presents the ratio of the actual GRP per population in 2017 to the calculated turning point based on the analytical results regarding the EKC for each province or city.

Table 5. Calculated Turning Points of EKC; unit: 100 million CNY.

Region	2017 PGRP	Ln (2017 PGRP)	Turning Point	Ratio
Beijing	128,994	11.768	2.944	1.334
Tianjin	118,944	11.686	2.735	1.306
Shanghai	126,634	11.749	1.205	1.114

Note: The turning point is the calculated inflection point of EKCs from the GWR results. The ratio is calculated by equation: 1 + (PCGRP2017 − Turning point)/Turning point. The ratio 1.000 means that the PGRP in 2017 reached the turning point. The turning point is calculated only for the regions with significant EKCs—Beijing, Tianjin, and Shanghai—that show a statistically significant inverted U-shape.

From these estimates, it is possible to simulate the trend in sustainable development after the analysis periods. Specifically, a ratio over 1.00 indicates that the GRP per population reached a calculated turning point. The pollutants start to decrease after this point, along with economic growth; therefore, it is possible to understand the condition of pollutants on the EKC of each province or city. Since the GWR results indicate significant spatial heterogeneity, only three big cities—Beijing, Tianjin, and Shanghai—passed their turning points. Their ratios were 1.334, 1.306, and 1.114, respectively. In these developed cities, significant political efforts and investment were made to improve the environmental quality. Consequently, these cities are more likely to achieve sustainable development than other regions.

In light of these findings, it is still difficult to define the relationship between economic growth and haze for other provinces or cities. It is possible that there are different shapes, not only for EKCs, but also for other relationships, such as linear relationships. Thus, a long-term analysis is needed for these provinces or cities, in order to capture the graph shapes of the relationship between economic growth and environmental pollutants.

4. Conclusions and Policy Recommendation

This study examined the EKC in China, focusing on both average relationships and spatial heterogeneity. The study applied the global models and the GWR model using the data regarding the haze in about 31 provinces or cities in China from 2000 to 2014. Using the GWR model, we explored the non-stationary spatial characteristics, since this model can be fitted to each data point and weighs all the observations as functions of distance from the regression point. As a result, it was possible to obtain local coefficients that varied spatially [20–25]. Based on the results of the GWR model, this study verified the existence of the EKC among regions and calculated the turning point by applying the real 2017 GRP per population data.

This study provided convincing evidence that the GWR model is valid for explaining the spatial heterogeneity of the EKC in China more effectively than the global models. The spatial variability test also confirmed that all the variables used in this study have spatial variability. The GWR model could determine the existence of an EKC for the haze and its spatial variations in China. Based on the empirical results from the GWR analysis, this study visualized the local coefficients and estimated the turning points of the EKCs. The results provided empirical evidence that only the three most developed regions in China—Beijing, Tianjin, and Shanghai—have statistically significant EKCs. Furthermore, the estimated turning points of the EKCs show that Beijing, Tianjin, and Shanghai have already passed their turning points. However, it was difficult to find an EKC for the remaining 28 provinces and cities. Moreover, the results indicated that there was no EKC for the haze in the three regions—Anhui, Jiangsu, and Ningxia.

The empirical results from the research period show that although three developed cities—Beijing, Tianjin, and Shanghai—showed a positive relationship between economic and environmental performance, while other regions were still suffering from the vicious cycle of air pollution. To achieve harmony between t environmental and economic development, it is necessary to find an effective way to achieve balanced economic growth by considering the spatial heterogeneity of the levels of development and pollution. The Chinese authorities are trying to find a way to balance productivity with pressing environmental issues through their policies and subsequent economic plans, in order to ensure the sustainability of China's economy. For example, there are environmental regulations regarding air pollution in China, such as the Two-Control Zone policy, which was established in 1998 to define acid rain control zones in the southern regions and SO_2 control zones in the north-eastern regions in China. Moreover, the Chinese government announced regulations on environmental protection, such as the Taxation Law on Environmental Protection and the Law on the Prevention and Treatment of Water Pollution to consider environmental degradation [39].

The empirical results of the current study show that the policies and laws regarding the prevention and control of atmospheric pollution need to be improved. Stronger macroeconomic regulations and control measures to promote the transformation of enterprise development can be effective. This study found significant spatial heterogeneity, confirming the EKC relationship between air quality and economic growth only in three big cities. In other words, most regions in China are still far from achieving sustainable development. From these findings, region-specific policies should be established to consider regional differences. For example, it would be effective for policymakers to tighten environmental regulations on air pollution, especially in statistically significant no EKC regions, such as Anhui, Jiangsu, and Ningxia. Additionally, monitoring and evaluation systems, including the management of haze indexes, are needed to ensure long-term effectiveness. Enhancing financial support and updating haze indexes in a timely manner can be also effective methods to improve air quality.

In addition, the Chinese government is trying to shift the development focus to balanced economic growth by converting the country's energy structure [40]. As part of these efforts, renewable energy laws and policies were established by the National Energy Administration to improve China's energy consumption structure. The Renewable Energy Law is an example of these efforts [41]. Since one of the main sources of haze is coal consumption, reforming the old pattern of long-term economic transformation from a "high-carbon" to a "low-carbon" economy will be effective [28]. To change the original energy consumption structure, active step-by-step actions must be taken to explore new low-pollution energy sources to reduce the consumption of fossil fuels [42].

Although this study provides empirical evidence for the spatial heterogeneity of the EKC for the haze in China, there is still room for improvement. This study applied the haze levels measured in API per capita in one representative station of each region. Estimation using API microdata in specific monitoring stations can be more effective for grasping the spatial heterogeneity of the EKC in China. Moreover, the factors that affect haze were not comprehensively evaluated in this study. For example, energy structure, industrial structure, capital intensity, and environmental management capacities can be considered. These factors were not evaluated mostly due to the existence of multicollinearity and data availability. Thus, it may be necessary to investigate more socio-economic factors and specify them both theoretically and statistically to design effective policies to achieve balanced economic growth in China. Furthermore, further studies could investigate the relationship between environmental quality and economic performance with more advanced models and data, such as through the use of the Distance between Indices of Simulation and Observation, which is a new comprehensive index presenting the overall performances of different models [43,44]. A comprehensive approach to determining regional trends and the current state of pollution will help to inform future policy on sustainable development in China.

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