Article

Analysis of Spatial Heterogeneity and the Scale of the Impact of Changes in PM_{2.5} Concentrations in Major Chinese Cities between 2005 and 2015

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Abstract: Deteriorating air quality is one of the most important environmental factors posing significant health risks to urban dwellers. Therefore, an exploration of the factors influencing air pollution and the formulation of targeted policies to address this issue are critically needed. Although many studies have used semi-parametric geographically weighted regression and geographically weighted regression to study the spatial heterogeneity characteristics of influencing factors of PM_{2.5} concentration change, due to the fixed bandwidth of these methods and other reasons, those studies still lack the ability to describe and explain cross-scale dynamics. The multi-scale geographically weighted regression (MGWR) method allows different variables to have different bandwidths, which can produce more realistic and useful spatial process models. By applying the MGWR method, this study investigated the spatial heterogeneity and spatial scales of impact of factors influencing PM_{2.5} concentrations in major Chinese cities during the period 2005–2015. This study showed the following: (1) Factors influencing changes in PM_{2.5} concentrations, such as technology, foreign investment levels, wind speed, precipitation, and Normalized Difference Vegetation Index (NDVI), evidenced significant spatial heterogeneity. Of these factors, precipitation, NDVI, and wind speed had small-scale regional effects, whose bandwidth ratios are all less than 20%, while foreign investment levels and technologies had medium-scale regional effects, whose bandwidth levels are 23% and 32%, respectively. Population, urbanization rates, and industrial structure demonstrated weak spatial heterogeneity, and the scale of their influence was predominantly global. (2) Overall, the change of NDVI was the most influential factor, which can explain 15.3% of the PM_{2.5} concentration change. Therefore, an enhanced protection of urban surface vegetation would be of universal significance. In some typical areas, dominant factors influencing pollution were evidently heterogeneous. Change in wind speed is a major factor that can explain 51.6% of the change in PM_{2.5} concentration in cities in the Central Plains, and change in foreign investment levels is the dominant influencing factor in cities in the Yunnan-Guizhou Plateau and the Sichuan Basin, explaining 30.6% and 44.2% of the PM_{2.5} concentration change, respectively. In cities located within the lower reaches of the Yangtze River, NDVI is a key factor, reducing PM_{2.5} concentrations by 9.7%. Those results can facilitate the development of region-specific measures and tailored urban policies to reduce PM_{2.5} pollution levels in different regions such as Northeast China and the Sichuan Basin.

Keywords: PM_{2.5}; spatial heterogeneity; multi-scale geographically weighted regression; differentiated governance

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1. Introduction

PM_{2.5} refers to a particulate matter in the atmosphere with a diameter less than or equal to 2.5 micrometers. PM_{2.5}, which has a significant impact on air quality and visibility, can travel directly to the alveoli of the lungs. Compared with coarse atmospheric particulate matter, smaller-sized PM_{2.5} particles contain a large number of toxic and harmful substances. These substances characteristically demonstrate longer residence times and conveying distances, thus having a greater impact on human health and atmospheric environmental quality [1,2]. Lots of studies have shown that they are responsible for the increased incidence of acute respiratory infections, lung cancer, asthma, and chronic obstructive pulmonary disease [3–7]. Therefore, short-term [8,9] and long-term exposure to PM_{2.5} increases mortality risks from cancer asthma [1,3,6], ischemic heart disease [1,3,6], stroke [1,6], and other medical conditions [1,3,6,9–11]. In the current context of climate change, the likelihood of extreme precipitation events occurring is also increased by high PM_{2.5} concentrations [12].

In recent years, as a result of rapid urbanization, the proportions of urban populations in relation to the total populations of countries are increasing. It has been estimated that by 2050, the global urban population will account for approximately 70% of the total population, while China's urban population will exceed 70% by 2030 [13]. Given that the quality of urban air directly affects the well-being of the vast majority of the world's population, PM_{2.5} reduction has become a hot research topic worldwide. However, an understanding of the mechanism behind changes in PM_{2.5} concentrations is necessary to regulate PM_{2.5} levels.

Many scholars have analyzed the spatial variation of PM_{2.5} in China from different scales such as daily scale [14–16], seasonal scale [14,15], and annual scale [14], and they revealed the physical mechanism behind PM_{2.5} pollution. Some authors analyzed the influencing factors of spatial distribution of PM_{2.5} concentration from the perspective of different factors. For example, Cheng et al. [17] analyzed from the perspective of FDI (foreign direct investment) found that the effects of FDI on urban PM_{2.5} have obvious heterogeneity. Zhou et al. [18] analyzed the relationship between PM_{2.5} and social economic factors (population density, industrial structure, industrial density, and road density) based on the data of 945 cities in China. Xiao et al. [7] analyzed influencing factors on PM_{2.5} spatial distribution including population, NDVI, wind speed, GDP (gross domestic product), precipitation, and so on, and they found that NDVI was closely related to PM_{2.5}. Other studies have shown that meteorological factors have an important impact on air pollution [16,19–21]. However, there was still a lack of analysis on the scale of impact factors in the existing studies. In addition, although many studies have revealed the spatial heterogeneity of influencing factors, they are often based on specific zoning or fixed bandwidth analysis and contain a lot of subjective factors.

Evident differences in the functional positioning and levels of economic development of different regions and cities are associated with variations in technologies and levels of industry, traffic, and anthropocentric heat emissions, leading to diversity in relation to the main factors affecting PM_{2.5} levels. In addition, combinations of these influencing factors may vary in different geographical locations, and their inter-relations may also evidence spatial inconsistencies [22,23]. Different geographical locations are associated with differing structures or relationships among these factors. Moreover, among the factors that influence PM_{2.5} concentrations, natural factors, such as wind speed, precipitation, and surface vegetation, exhibit spatial heterogeneity [19,21,24–27]. Such spatial heterogeneity may be significant within a certain regional zone, but it may not be significant beyond a certain range [28]. Furthermore, some factors may have cross-regional impacts, so different impact factors may present differential effects according to their spatial scale. Goodchild [29] and McMaster [30] emphasized the importance of considering scale within geographical studies of all kinds. Accordingly, an urgent scientific problem concerns the scientific measurement of the spatial heterogeneity and scale of influence of factors that affect PM_{2.5} concentrations.

These measurements can aid the development of regionally differentiated haze reduction measures and joint prevention and control strategies.

Previous studies have generally verified the spatial heterogeneity of certain factors influencing $PM_{2.5}$ concentrations [24,31]. Some scholars have distinguished various regional influencing factors from the perspective of existing natural or artificial zones. However, these studies, which are based on existing zones, do not shed light on the cross-regional influences of some of the factors. Other scholars have conducted analyses applying ordinary least square regression (OLS) or classical geo-weighted regression (GWR) [27,32]. Although the use of these two methods can reveal spatial heterogeneity, GWR, in particular, is better suited to identifying the geographical elements of spatial heterogeneity [27,33]. Moreover, the fixed bandwidths used for GWR are inadequate for explaining the issue of “scale” and revealing the impact factors of different spatial scales due to capture the excessive noise results unsound [34]. Although semi-parametric geo-weighted (SGWR) regression can handle problems relating to global and local scales [35,36] to some extent, it cannot be used to further subdivide the impact scales of different variables beyond the initial division into global and local categories [37]. In light of the above issues, Fotheringham [38] proposed a multi-scale geographically weighted regression (MGWR) method to resolve the problems of cross-geographical factors and cross-scales. However, the statistical inference method used for the model was inadequate. Consequently, Yu et al. [39], Li, and Fotheringham [40] later supplemented and improved the statistical inference method used for the MGWR. The main MGWR has several advantages over the traditional classical GWR [40]. First, MGWR allows for different levels of spatial smoothness for each variable, thereby resolving drawbacks associated with the classical GWR model. Second, the specific bandwidth of each variable can be used as an indicator of the spatial scale of the action of each spatial process. Third, a multi-bandwidth approach produces a more realistic and useful spatial process model [31]. Currently, the MGWR-based research methodology has proved to be a reliable method for revealing the spatial heterogeneity of geographical elements in areas such as housing prices forecasts [37], air quality [31], and the selection of the locations of manufacturing industry [39]. However, empirical studies that have used this method to examine the spatial heterogeneity and scale of impact of factors that influence $PM_{2.5}$ remain limited.

Accordingly, this study applied the MGWR model using natural and socioeconomic data to determine factors influencing $PM_{2.5}$ concentrations and to explore their spatial heterogeneity and the scale of changes in $PM_{2.5}$ concentrations in major cities in China during the period 2005–2015. In addition, the study attempted to rank these factors in terms of their importance in major cities. In light of the results of the MGWR, the study applied hierarchical partitioning analysis to rank the importance of factors that evidenced significant spatial agglomeration. The aim of this study was to address the following questions and to provide a scientific basis for differentiated governance and the formulation of measures adapted to local $PM_{2.5}$ conditions in major Chinese cities. The first question focused on whether the main factors influencing changes in $PM_{2.5}$ concentrations in major Chinese cities exhibited spatial heterogeneity during the period 2005–2015 and the extent of the scale of their influence. The second question related to how the main influencing factors in typical regions evidencing significant spatial agglomeration effects were ranked relative to each other.

2. Materials and Methods

2.1. Data Sources

2.1.1. Selection of Variables

Prefecture-level cities across China constituted the basic research unit (Figure 1), and the change (slope) of $PM_{2.5}$ concentrations from 2005 to 2015 were considered the dependent variable. The independent variables were natural and socioeconomic influencing factors. Natural factors were precipitation (PRE), wind speed (WIN), and the Normalized Difference Vegetation Index (NDVI). Social and economic factors were the urbanization

rate (UR), the urban population density (POP), per capita industrial production (PCIP), the proportion of the output value of secondary industry (SecI) in relation to the Gross Domestic Product (GDP), foreign investment levels (FIL), the proportion of science and technology expenditure (TEC), energy intensity (EngI), and environmental control intensity (ECI) (Table 1).

These variables were selected based on the following: UR was expressed as the ratio of the annual non-agricultural population to the total population. The degree of pollution is usually lower during a period when the UR is low. Along with the urbanization process, production and living activities bring about more energy; at the same time, the cement and building materials required for construction, which is integrally linked to industrial uses and the urbanization process, may exacerbate PM_{2.5} pollution [28]. A higher population density per unit area (POP) in a city corresponds to greater energy consumption through production and living, higher emissions of pollutants, and higher probabilities of air pollution [41]. PCIP was expressed by the level of industrial development. Compared with industrially underdeveloped areas, industrially developed areas have higher degrees of industrial pollution [42]. SecI was expressed as the industrial structure. Secondary industries are major energy consumers and pollutant emitters. Under the same economic aggregate, a higher proportion of secondary industries is associated with greater direct and indirect impacts of energy consumption and PM_{2.5} emissions [28,42,43]. FIL often signifies the level of openness to the outside world. A higher ratio of total investments of foreign-invested enterprises to the GDP is associated with the use of advanced technologies and equipment for environmental protection acquired from abroad and increased foreign investments in China's environmental protection industry [18,42]. TEC generally influences the production process through the adoption of equipment and technologies such as desulfurization, denitrification, and dust removal [21]; technologies for cleaning fossil energy sources, such as coal and petroleum; and methods of managing green and intensive energy production and consumption. It is expressed as the proportion of the total expenditure on technology within the city's total financial expenditure. Higher levels of technology are associated with more advanced production equipment and less air pollution. Technological progress is an important factor in environmental governance and improvement of the environment. EngI was expressed as the proportion of industrial power consumed in relation to the total industrial output value. A higher proportion of secondary industries is associated with higher energy consumption in the production process and a higher value of EngI, which plays a role in the intensification of PM_{2.5}. ECI was expressed as the ratio of investments in industrial pollution control to the GDP. It is mainly used to solve the externality of environmental pollution. International experience shows that strengthening environmental regulations is conducive to reducing the probability of PM_{2.5} weather occurrence. The diffusion of PM_{2.5} particulate matter is affected by natural factors, such as air mobility and precipitation [12]. Higher wind speeds (WIN) correspond to greater air mobility, which enables the dissipation of PM_{2.5} [44]. Higher levels of precipitation (PRE) are associated with a lower probability of haze occurrence [45]. In addition, haze is affected by surface vegetation coverage. Vegetation can not only purify the air but also prevent wind and fix sand to reduce PM_{2.5} pollution. Furthermore, forests and grassland have different adsorption capacities relating PM_{2.5} [26], and high levels of vegetation coverage also contribute to air purification and the mitigation of haze pollution. Finally, NDVI was represented by land cover, which has a close relationship with PM_{2.5} concentration [21,46].

Figure 1. The study area. The red dots represent 275 major prefecture-level cities.

Table 1. Description of variables.

Variables		Abbreviations	Variable Description
The dependent variable	PM _{2.5}	PM _{2.5}	Particulate matter with a diameter of less than 2.5 microns can enter the lungs, expressed as fine particulate matter, in terms of the annual average concentration of micrograms per cubic meter
	Urbanization Rate	UR	Non-agricultural population/Total population in cities (%)
The independent variables	Urban population density	POP	Total urban population/urban administrative unit area at the end of the year (person/km ²)
	Per capita industrial production	PCIP	Industrial output value/year-end total population (yuan/person)
	Socioeconomic indicators	SecI	Output value of secondary industry/GDP (%)
	Secondary industry in proportion to Gross Domestic Product	FIL	Actual utilized foreign capital/GDP (%)
	Foreign investment level	TEC	Science and technology expenditure/Fiscal expenditure (‰)
	The level of science and technology	EngI	Industrial power consumption/total industrial output value (10,000 kW·h/100 million yuan)
	Energy intensity	ECI	Environmental investment/GDP (%)
Natural indicators	Environmental control intensity	PRE	Average annual precipitation of urban administrative unit (mm)
	Precipitation	WIN	Average annual wind speed of urban administrative unit (m/s)
	Wind speed	NDVI	(near infrared – infrared)/(near infrared + infrared)
	Normalized difference vegetation index		

2.1.2. Data Sources

The PM_{2.5} data in this study were obtained from the Socioeconomic Data and Applications Center (<https://sedac.ciesin.columbia.edu/search/data?contains=PM2.5>, accessed on 30 December 2019), and its spatial resolution is 1 km, which is sufficient for

an urban scale. The NDVI data were derived from the product data of each month and annually compiled and synthesized normalized difference vegetation index values (https://lpdaac.usgs.gov/product_search/?query=NDVI&view=cards&sort=title, accessed on 30 December 2019), which had a spatial resolution of 1 km. Wind speed and precipitation data were extracted from historical monitoring data compiled by the National Meteorological Center of China (<http://data.cma.cn>, accessed on 30 December 2019), and the spatial grid was based on ANUSPLIN interpolation. In addition, resampling data based on annual city boundaries were obtained. Data on industrial output values, population densities, urbanization rates, industrial structures, foreign investment levels, environmental control intensity, and technological levels were derived from national population statistics for Chinese counties and cities, *China City Statistical Yearbooks*, Regional Economic Statistics Yearbooks, prefecture-level statistical yearbooks, and environmental statistical bulletins for the period 2006–2016. The missing data for individual indicators were supplemented through linear interpolation. As a result of data limitations, Taiwan, the Tibet Autonomous Region, Hong Kong, and the Macao Special Administrative Region were not included in the study. A total of 275 cities were covered in the study.

2.2. Methodology

2.2.1. Linear Regression Analysis

Linear regression analysis was performed to calculate changes relating to PM_{2.5}, UR, POP, PCIP, SecI, FIL, TEC, EngI, ECI, PRE, WIN, and NDVI for the period 2005–2015, and the change slope for each factor was obtained for this same period. Note that the spatial heterogeneity of natural factors itself does not mean that the rate of change of natural factors must be spatially heterogeneous. In this study, the changes slope for PM_{2.5} between 2005 and 2015 was treated as the dependent variable, the slopes of UR, POP, PCIP, SecI, FIL, TEC, EngI, ECI, PRE, WIN, and NDVI were input as independent variables in the model to calculate the impacts of various factors in major Chinese cities.

2.2.2. Multi-Scale Geographically Weighted Regression

The MGWR model was expressed as follows [34]:

$$y_i = \sum_{j=1}^k \beta_{buj}(u_i, v_i) x_{ij} + \varepsilon_i \quad (1)$$

where buj represents the bandwidth used by the regression coefficient of the j variable, (u_i, v_i) is the coordinate of i , x_{ij} is the independent variable, and ε_i is the residual.

The regression coefficient, β_{buj} , which was based on local regression, entailed a specific bandwidth, marking a key difference between MGWR and classical GWR models, in which the bandwidths of all variables are the same. However, MGWR and several classic GWR models share the same kernel and bandwidth selection criteria. This study adopted the most widely used quadratic kernel functions and AICc as guidelines. The back-fitting algorithm was used to fit each smooth item. This algorithm requires the initialization of all smoothing items, which means that preliminary estimates of the coefficients in the MGWR model need to be made prior to applying the algorithm. The classic GWR estimation method was chosen for the initial estimate. After determining the initialization settings, the study was able to calculate the disparity between the true value and the estimated predicted value based on the initialization residue.

In this study, the bandwidths of different influencing factors were used to assess their scale effects. The bandwidth of each factor was calculated using the model to obtain the optimal bandwidth [47]. The golden section was applied to search for the optimal bandwidth value of each influencing factor by continuously narrowing the value range of the optimal value and comparing the optimization scores for each model. To avoid the issue of contingency relating to changing influencing factors and to increase the reliability of the results relating to the spatial heterogeneity of these factors, authors performed the

Monte Carlo test to evaluate the results obtained using the model [40]. The local parameter estimation was obtained by performing the Monte Carlo test, and then, new local parameter estimations were repeatedly obtained following random rearrangements of the data points to measure whether the change in each parameter's surface was likely to have occurred accidentally. In this study, the Monte Carlo test tool that comes with MGWR software was used.

2.2.3. Hierarchical Partitioning Analysis

Hierarchical partitioning (HP) analysis was performed to identify the independent effects of explanatory variables contained in the model. HP entails semi-parametric regression analysis and is used to calculate the relative importance of each factor by performing multiple random transformations of the original data matrix. This method is considered appropriate for overcoming multicollinearity, which often occurs with the use of environmental variables. Compared with traditional methods of regression analysis, HP is more suitable for analyses of multidimensional environmental data [48,49]. The authors applied HP analysis to determine the importance of independent influencing factors and rank them in terms of their impacts on spatial variations in the concentration of $PM_{2.5}$. This assessment enabled the identification of key influencing factors and could provide inputs in the formulation of feasible governance schemes for regulating $PM_{2.5}$ levels.

3. Results and Discussion

3.1. Spatial Distribution Pattern of $PM_{2.5}$

Figure 2a reveals a distinct pattern of spatial variation regarding changes in the $PM_{2.5}$ concentrations in major Chinese cities during the period 2005–2015. The increasing trend in $PM_{2.5}$ concentrations was mainly evident in the northern and northeastern regions of China, in Inner Mongolia, in the middle and lower reaches of the Yangtze River, and in Yunnan Province. The average annual increase of $PM_{2.5}$ was at least 0.02 ug/m^3 , and the maximum increase can reach 3.8 ug/m^3 in those areas. It was particularly prominent in the three northeastern provinces (Heilongjiang, Jilin, and Liaoning) and in the provinces of Anhui and Jiangsu, the annual increase in $PM_{2.5}$ concentration in these areas exceeds 0.6 ug/m^3 . This finding is consistent with those of Xue et al. [50] and Zhang et al. [28]. The main regions evidencing reduced $PM_{2.5}$ concentrations were the Sichuan Basin, the Yunnan-Guizhou Plateau, and the southern provinces south of the Yangtze River. The annual reduction in $PM_{2.5}$ concentration in these areas can reach 0.5 ug/m^3 . The reduction trend was most apparent in major cities in the Sichuan Basin and in Hunan Province (the maximum reduction can reach about 2 ug/m^3 per year), which is consistent with the findings of He and Zhang as well as Yang et al. [42,51]. To confirm the advantages of the MGWR method over the GWR method, this study compared the operation results obtained using the two methods. The results are shown in Appendix A, Table A1. The R^2 value adjusted using the MGWR model was larger than that obtained with the GWR model, and the AICc and the residual sum were lower using the former method. These results confirm that the simulation results obtained using the MGWR model was more accurate than that obtained using the GWR model. As shown in Figure 2b, the application of the MGWR method revealed changes in the spatial distribution pattern of $PM_{2.5}$ concentrations in China's major cities; the explanatory power is all above 65.5% ($R^2 > 0.655$); the national average of R^2 is 0.844. Moreover, the use of the MGWR model resulted in smaller residual errors (Figure 2c) compared with errors obtained using the GWR method (Figure 2d). The analysis of cold and hot spots revealed regions with evident high and low values of $PM_{2.5}$ concentrations in their major cities (Figure 2e). High-value regions comprised the cities of the three northeastern provinces and some of the cities in the provinces of Anhui and Jiangsu. Low-value regions comprised major cities in the Sichuan Basin and in Hunan and Guangdong Provinces. Both the high and low values passed the 99% significance level.

Figure 2. The spatial distribution of changes in PM_{2.5} concentrations in major Chinese cities from 2005 to 2015. Spatial distribution characteristics of PM_{2.5} (a); Spatial distribution of R^2 (b); Residual of MGWR (c); Residual of GWR (d); Analysis of cold and hot spots of PM_{2.5} (e).

3.2. Results of the Analysis of the Scale Effects of Influencing Factors

The effects of spatial scale were determined on the basis of the bandwidths of the different influencing factors obtained after conducting the MGWR regression [47]. Smaller (larger) bandwidths corresponded to smaller (larger) scales of impact. In this study, authors focused on the city scale and regional scales. Therefore, to present the scales of influence for each variable more clearly, this study redefined the scales according to the proportions of variable bandwidths. The proportions of the bandwidth ranges were defined as small regional scale (0–20%), medium regional scale (20–40%), larger regional scale (40–60%), and national or global scale (>60%).

It can be seen from Figure 3 and Table A2 that there were discrepancies in the impact scales for different variables. The overall coefficients of the intercept (constant term), PRE, NDVI, WIN, FIL, and TEC were significant in the MGWR regression results and passed

the Monte Carlo significance test ($p < 0.05$), whereas the regression coefficients of the SecI, ECI, POP, EngI, PCIP, and UR variables were not significant (Figure 3, Table A3). The bandwidth of the intercept was less than or equal to 43, accounting for about 16% of the total sample (a small regional scale). Since many factors affect the change of PM_{2.5} concentration, this study only selected some representative factors (Table 1), and the omitted variables were inevitable. The study by Shen et al. [37] showed that the omitted variables can be reflected in the intercept term when basing on the method of geographically weighted regression. The intercept term indicated that different omitted variables would influence the dependent variable (change in PM_{2.5} concentration) [37]. As Figure 3 shows, the intercept term had the smallest bandwidth, indicating that changes in PM_{2.5} concentrations are sensitive to intercept. Thus, PM_{2.5} concentrations would change dramatically for bandwidths above 43. The study by Yu et al. [39] showed that the change in intercept may be related to the location change. The bandwidth of the intercept is 43, which means that the location factor including the omitted variable has strong spatial heterogeneity. This finding is consistent with the study results of Xia et al. [21], which further illustrates the rationality of the results of this study. The bandwidths of PRE, NDVI, and WIN (43, 47, and 49, respectively) were also small, accounting respectively for about 16%, 17%, and 18% of the total number of samples, indicating a small regional scale of influence for these three variables. All three factors were natural factors, indicating that natural factors significantly influence changes in PM_{2.5} concentrations and exhibit considerable spatial heterogeneity. The FIL and TEC bandwidths were 62 and 89 respectively, accounting for 23% and 32% of the total number of samples, thus falling within the medium regional scale. The remaining variables did not pass the significance test, indicating that there was no spatial heterogeneity or that their scale of influence was global. In general, the scale of influence was more sensitive for natural factors than for socioeconomic factors that affected changes in PM_{2.5} concentrations in major Chinese cities from 2005 to 2015.

Figure 3. The bandwidth percentage for each impact factor in the total number of samples. The blue bar represents the small regional scale, the green bar represents the medium regional scale, the purple bar represents the large regional scale, and the red bar represents the global scale. *** denotes 99% confidence that passes the Monte Carlo significance test, ** denotes 95%. From left to right on the X axis, the bandwidth is increasing.

Compared with some studies, the results can better reflect the transregional effects of some influencing factors. For example, the Sichuan Basin is a complete topographic unit, but the SECI factor was also significant in the Sichuan Basin and some surrounding areas outside the basin, indicating that SECI had trans-regional effects. Since each city can have

a corresponding result, decision-makers in different cities can formulate mitigation policies based on the priorities of different impact factors to a certain extent.

3.3. Results of the Analysis of the Spatial Heterogeneity of Influencing Factors

3.3.1. Spatial Heterogeneity of Influencing Factors from a Global Perspective

Table 2 provides statistical descriptions of the coefficients and shows that the constant term had positive or negative effects on changes in PM_{2.5} concentrations and that significant spatial heterogeneity was associated with a negative mean value. It can be seen from Figure 4a that changes in the positive and negative values of the constant term were strongly related to geographical locations. The greatest reduction in PM_{2.5} concentrations occurred in Guangdong and Hainan Provinces in southern China, while the greatest increase occurred in northeastern China. Moving from south to north, changes in PM_{2.5} concentrations showed a gradual increase trend, and this spatial distribution pattern was especially apparent in eastern China. It may have been affected by the topography of this region [20], with the reduction in PM_{2.5} in the Sichuan Basin being more obvious than it was in Yunnan, which is at a lower latitude. However, the overall trend in areas north of the Sichuan Basin conformed to the pattern of change entailing increased PM_{2.5} concentrations moving from south to north. This pattern indicates that geographical location significantly influences the spatial distribution pattern of changes in PM_{2.5} concentrations [20], with the minimum constant term bandwidth shown in Figure 3 further indicating significant spatial heterogeneity in the influence of location.

Table 2. Summary statistics for MGWR parameter estimates.

Variable	Mean	STD	Min	Median	Max
Intercept	−0.071	0.585	−0.675	−0.257	1.573
POP	−0.025	0.024	−0.073	−0.019	0.003
UR	0.013	0.004	0.001	0.015	0.018
PCIP	0.031	0.005	0.022	0.031	0.045
SecI	−0.023	0.112	−0.28	−0.023	0.293
FIL	−0.094	0.152	−0.48	−0.068	0.187
TEC	−0.056	0.095	−0.283	−0.028	0.077
EngI	0.019	0.012	−0.013	0.023	0.034
ECI	0.018	0.039	−0.077	0.034	0.072
PRE	−0.092	0.145	−0.737	−0.104	0.192
WIN	−0.013	0.149	−0.28	−0.016	0.308
NDVI	−0.153	0.276	−0.766	−0.112	0.468

Figure 4. Spatial patterns of coefficients in the MGWR. The colored solid points denote cities that passed the 95% significance test ($p < 0.05$), and the gray solid points denote cities that did not pass the 95% significance test ($p > 0.05$). Interception (a); Technological progress (b); SecI (c); FIL (d); WIN (e); Precipitation (f); and NDVI (g). Note that only the coefficients of factors with significant spatial heterogeneity ($p < 0.05$) are shown in the figure.

The SecI, ECI, POP, EngI, PCIP, and UR variables did not pass the 95% significance test, indicating very weak or non-existent spatial heterogeneity relating to the influence of these variables on changes in PM_{2.5} concentrations. Furthermore, as revealed by the bandwidths of these variables (Figure 3), their effects were likely to be global. The PRE, NDVI, WIN, FIL, and TEC variables passed the Monte Carlo significance test (95%), revealing significant spatial heterogeneity in their influence on changes in PM_{2.5} concentrations. As shown in Table 2, the influence of these variables on changes in PM_{2.5} concentrations was either positive or negative, indicating that they were associated with increased PM_{2.5} pollution in some cities and reduced PM_{2.5} pollution in other cities. However, the average coefficient of TEC was -0.056 , indicating that on the whole, increased investments of technical funds could be beneficial for reducing PM_{2.5} concentrations. The average SecI coefficient was -0.023 , indicating that PM_{2.5} concentrations would be lower with increasing values of industrial outputs in proportion to the GDP. There was little variation in this negative effect across cities, and the intensity of its influence was relatively weak. The coefficient of FIL changed from -0.48 to 0.187 , indicating that the influence of FIL varied in different cities, which evidenced positive as well as negative influences. The mean value was -0.094 , which implied that on the whole, reductions in PM_{2.5} pollution were more likely to occur with higher levels of actually utilized foreign capital in proportion to the GDP. The PRE coefficient ranged from -0.737 to 0.192 , indicating that the influence of precipitation in different cities also evidenced spatial heterogeneity, with a mean value of -0.092 . Therefore, the overall influence of precipitation on PM_{2.5} concentrations was negative, with greater precipitation associated with lower levels of PM_{2.5} pollution. The mean coefficient of WIN was -0.013 , indicating that wind had a positive influence in the diffusion of PM_{2.5}. To prevent an increase in PM_{2.5} pollution, appropriately designed wind corridors could be incorporated into urban planning. The average coefficient of NDVI was -0.153 , indicating that conditions entailing a high-level surface vegetation coverage are favorable for reducing PM_{2.5} levels.

Since all of the variables had been z-score standardized prior to conducting the MGWR regression, the sizes of the coefficients obtained could be compared. Higher absolute values of the coefficients corresponded to an increase in the influence of the associated variable on changes in the PM_{2.5} concentration. The study selected variables that passed the $\geq 95\%$ significance test, namely PRE, NDVI, WIN, FIL, and TEC. As shown in Table 2, the absolute values of the coefficients in descending order were NDVI (0.153) > FIL (0.094) > PRE (0.092) > TEC (0.056) > WIN (0.013). These values indicate that NDVI had the greatest effect on changes in PM_{2.5} concentrations in China's major cities during the period 2005–2015, which can explain 15.3% of the change in PM_{2.5} concentration. Thus, afforestation and increased protection of vegetation during the urbanization process can substantially alleviate PM_{2.5} pollution in most cities of China.

3.3.2. Spatial Heterogeneity of Influencing Factors from a Local Perspective

To foster a more intuitive perception of the spatial distribution characteristics of variables evidencing significant spatial heterogeneity, the study extracted cities for which all of the variables passed the 95% significance test and plotted them on a map (Figure 4). Solid colored points in Figure 4 represent cities that passed the 95% significance test, while gray solid points represent cities that did not pass the 95% significance test. As Figure 4 shows, cities could only be extracted with reference to variables demonstrating strong spatial heterogeneity, namely the intercept term, NDVI, FIL, PRE, TEC, SecI, and WIN. As shown in Figure 4a, the spatial heterogeneity of locations was highly significant. Different land and sea locations and different latitudes all impact on PM_{2.5} concentrations, and a gradual trend of change from a negative to a positive direction was evident for locations moving from southern to northern regions. It is apparent from Figure 4b that the spatial heterogeneity associated with TEC was most significant in cities in the northeastern provinces and other regions, namely Heilongjiang, Jilin, Liaoning, Beijing–Tianjin–Hebei, Shanxi, and Yunnan. In these regions, increasing investments in science and technology

could significantly reduce $PM_{2.5}$ concentrations. The spatial heterogeneity of $SecI$ was mainly observed in major cities located in the Sichuan Basin and nearby cities (Figure 4c). The diffusion of pollutants is impeded by the high terrain surrounding the Sichuan Basin. Intensive production in this region and the improvement of its industrial annex value could lead to a significant reduction in $PM_{2.5}$ pollution. The spatial heterogeneity associated with the influence of FIL on $PM_{2.5}$ concentrations was mainly observed in some inland cities, notably in the Yunnan–Guizhou Plateau, the Sichuan Basin, and in Gansu and southern Shaanxi, as well as in major cities in Shanxi, southern Hebei, western Shandong, and Henan (Figure 4d). The effect of FIL in reducing $PM_{2.5}$ pollution became increasingly apparent moving further inland, as shown in Figure 4d. Higher FIL means that more advanced technology and equipment can be obtained from abroad, which can not only improve industrial production efficiency but also save energy and reduce emissions to a certain extent [17]. Therefore, in these regions, higher ratios of actually utilized foreign capital to the GDP would have a favorable effect in mitigating $PM_{2.5}$ pollution. In the Sichuan Basin, the maximum value of the FIL coefficient can reach -0.38 to -0.48 , which means that for one-point increase in actually utilized foreign capital, the change in $PM_{2.5}$ concentration can be reduced by 0.38 – 0.48 (explanatory power was 75 – 79%).

WIN , PRE , and $NDVI$ were categorized as natural factors. The most significant levels of spatial heterogeneity relating to WIN were observed in major cities in the provinces of Heilongjiang and Jilin in northeastern China; the southern parts of Hebei, Shanxi, Henan, and Gansu Provinces; the western part of Jiangxi Province; the northeastern part of Guangxi Province; and the northern part of Guangdong Province. WIN had a positive influence in major cities in the central and northern parts of Henan Province, whereas it had a negative influence in other cities. The negative impact was most pronounced in major cities in the northeastern provinces of Heilongjiang and Jilin, in the northwestern province of Gansu, and in Hunan Province south of the Yangtze River. The cities where factors influencing $PM_{2.5}$ concentrations evidenced the most significant spatial heterogeneity were distributed in the Yunnan–Guizhou Plateau (in Yunnan Province, west of Guizhou); Henan, Hubei, and Hunan Provinces and in central China; the northern part of Fujian Province; and southeastern coastal regions, such as Zhejiang and Shanghai. In all of the above-mentioned cities, PRE 's influence was mainly negative. Higher levels of precipitation were associated with higher $PM_{2.5}$ clearance rates [45].

The influence of $NDVI$ on spatial heterogeneity overlapped with that of WIN and PRE , but there were also differences. Cities with the most significant spatial heterogeneity of $NDVI$ were distributed in the three northeastern provinces; in Zhejiang, Shanghai, Jiangsu, Shandong, Shanxi, Ningxia, and Gansu; in the Sichuan Basin; and in Yunnan in southwestern China. $NDVI$ had a slightly positive influence in major cities in the Sichuan Basin and Yunnan along the Yunnan–Guizhou Plateau, whereas in other cities, it had a negative influence. Afforestation and the protection of surface vegetation would have important effects in reducing $PM_{2.5}$ concentrations in the three northeastern provinces and in the eastern coastal areas and northwest China.

3.4. Ranking of Factors Influencing Changes in $PM_{2.5}$ Concentrations in Typical Regions

This study conducted an HP analysis to rank major independent factors influencing changes in $PM_{2.5}$ concentrations in major cities across China in order of their importance. The results of the MGWR regression enabled us to identify typical regions where two or more influencing factors overlapped spatially. Consequently, the study measured the importance of the influencing factors in typical regions according to changes in the factors' R^2 values in the HP analysis [48]. Changes in the R^2 value of a factor were indicative of its influence on changes in $PM_{2.5}$ concentrations. Thus, the study assessed the importance of the main factors influencing changes in $PM_{2.5}$ concentrations in the region for the period 2005–2015. HP analysis was considered suitable for determining the importance of influencing factors because the selected factors were spatially aggregated, indicating low

levels of intra-layer variance. Thus, the use of the HP method to calculate the specific areas is associated with minimal errors, resulting in relatively reliable findings.

The results of the MGWR revealed that typical regions with significant spatial agglomeration that passed the significance test were region A in the northeast (mainly Heilongjiang and Jilin Provinces), region B comprising the Central Plains (mainly Henan and Hebei Provinces), region C, comprising the Sichuan Basin, region D comprising the Yunnan-Guizhou Plateau (mainly cities in Yunnan), and region E, comprising cities in the lower reaches of the Yangtze River. Figures 5 and 6 respectively show the major cities and factors evidencing significant spatial heterogeneity in these regions. The study performed an HP analysis of the significant factors of these typical regions to determine changes in R^2 values and to sort these changes, as shown in Figure 6 and Table A4. Evidently, increasing investments in science and technology can contribute effectively to mitigating $PM_{2.5}$ pollution in region A ($\Delta R^2 = 0.320$) (Figure 4b). The increase in technology investment can lead to the improvement of industrial production efficiency and the reduction of pollutant emissions, which can play an important role in mitigating $PM_{2.5}$ pollution. In cities located in region B, the wind ($\Delta R^2 = 0.516$) plays an important role in reducing $PM_{2.5}$ pollution. Through inquiring data, the positive correlation between urban wind and pollutants in area B is related to the terrain. The southern part of area B is the Qinling Mountains and the Taihang Mountains in the northeast. Blocked by the mountains, when the northwest wind prevails in winter, the wind will carry sand in the desert and atmospheric pollutants emitted by industries along the way. Atmospheric conditions have favored an increase of air pollutants, thus exacerbating the pollution of cities in the region. Therefore, the construction of wind corridors as part of the urban planning process in this region should be prioritized. FIL was the most important factor in regions C ($\Delta R^2 = 0.306$) and D ($\Delta R^2 = 0.442$), indicating that increasing the proportion of actually utilized foreign capital in this region in relation to the GDP could greatly alleviate $PM_{2.5}$ pollution. Therefore, efforts should be made to encourage inflows of foreign capital for the future development of this region. In addition, the influence of TEC ($\Delta R^2 = 0.337$) in each city in region D merits attention. Increasing investments in science and technology in the industrial development process are also important for alleviating $PM_{2.5}$ pollution. In the lower reaches of the Yangtze River (region E), there was little difference in the impacts of NDVI ($\Delta R^2 = 0.097$) and PRE ($\Delta R^2 = 0.091$) on $PM_{2.5}$ pollution. Compared with precipitation, the direct impact of human activities on the surface vegetation is more heavier during the process of urbanization. Figure 4 shows that NDVI has a significant mitigating effect on $PM_{2.5}$ pollution in region E. It has been proven that the change of NDVI can be the dominant factor affecting the change of $PM_{2.5}$ concentration, although the region and time span of this study are different [46]. Therefore, the protection of vegetation and afforestation in the process of industrial development and rapid urbanization should be prioritized in this region. In the Sichuan Basin (C), the main factor influencing $PM_{2.5}$ concentrations is FIL, which is followed by SecI, indicating the need to strengthen foreign investments in this region and to adjust its industrial structure. Increasing industrial output values could significantly alleviate $PM_{2.5}$ pollution, which is consistent with the results of Ma et al.'s research [24]. The above findings can provide a scientific basis for developing region-specific measures to control $PM_{2.5}$ pollution according to local conditions.

Figure 5. Typical regions with significant spatial heterogeneity associated with factors influencing $PM_{2.5}$ concentrations: region A: the northeast region (with red solid dots); region B: the Central Plains (with green solid dots); region C: the Sichuan Basin (with blue solid dots); region D: the Yunnan-Guizhou Plateau (with dark blue solid dots); region E: the lower reaches of the Yangtze River (with yellow solid dots).

Figure 6. Ranking of the importance of influencing factors associated with significant spatial heterogeneity in typical regions: region A: the northeastern region; region B: the Central Plains; region C: the Sichuan Basin; region D: the Yunnan-Guizhou Plateau (most of the cities are located in Yunnan); region E: the lower reaches of the Yangtze River.

4. Conclusions

By applying the MGWR method, this study investigated the spatial heterogeneity and spatial scales of impact of factors influencing PM_{2.5} concentrations in major Chinese cities during the period 2005–2015. Compared with the previous studies, the biggest difference from the existing research is that this study used the method of MGWR, which searches the bandwidth adaptively and allows each variable to have its own most suitable bandwidth, which can reduce the influence of subjective factors to a certain extent, so it can produce a more realistic and useful spatial process model. The study also conducted an analytic hierarchy process to rank the leading factors in typical regions in terms of their importance. The following conclusions, derived from findings of this study, can provide a scientific basis for developing locally tailored measures to control PM_{2.5} pollution.

First, changes in PM_{2.5} concentrations in major Chinese cities between 2005 and 2015 evidenced a distinct pattern of spatial variation. Increases in PM_{2.5} concentrations were more pronounced in the three northeastern provinces (Heilongjiang, Jilin, and Liaoning) and in Anhui and Jiangsu, whereas reductions in PM_{2.5} concentrations were most pronounced in major cities located in the Sichuan Basin and in Hunan Province.

Second, the spatial heterogeneity and scales of influence of the five factors FIL, TEC, PRE, WIN, and NDVI on changes in PM_{2.5} concentrations were significant. Whereas the influences of the natural indicators PRE, NDVI, and WIN were more significant at a small regional scale, the influences of the socioeconomic indicators FIL and TEC mainly manifested as medium-scale regional effects. POP, UR, PCIP, SecI, EngI, and ECI evidenced weak spatial heterogeneity, and their impacts were mainly at the global scale.

Finally, the main factors influencing changes in PM_{2.5} concentrations at the global scale and in typical regions differed. From a global perspective, NDVI was the most important variable affecting changes in PM_{2.5} concentrations in major Chinese cities during the period 2005–2015. From the perspective of typical regions, in the northeast region, science and technology could play an important role in mitigating PM_{2.5}. Wind is an important factor in mitigating PM_{2.5} pollution in most cities located in the Central Plains; therefore, urban planning in this region should incorporate the construction of wind corridors. FIL was the main influencing factor in major cities in Yunnan Province and in the Sichuan Basin, indicating that increasing the proportion of foreign capital actually utilized in these regions as a percentage of the GDP would impact favorably on the reduction of PM_{2.5} pollution. In addition to FIL, SecI had a strong impact in the Sichuan Basin, indicating that efforts should be directed toward adjusting the industrial structure during the development process, with increasing industrial output values also contributing significantly to the alleviation of PM_{2.5} pollution.

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Appendix A

Table A1. Comparison of model indexes between MGWR and GWR.

Model Index	MGWR	GWR
Adjusted R ²	0.844	0.762
AICc	405.572	507.742
Effective number of parameters (trace(S))	80.15	74.706
Residual sum of squares	30.329	47.544

Table A2. MGWR bandwidths (bandwidth confidence intervals: 95%).

Variable	Bandwidth	ENP _j	Adj <i>t</i> -val(95%)	DoD _j
Intercept	43 (43.0, 47.0)	10.675	2.851	0.578
POP	237 (186.0, 254.0)	1.622	2.171	0.914
UR	274 (220.0, 274.0)	1.284	2.075	0.955
PCIP	274 (220.0, 274.0)	1.295	2.078	0.954
SecI	43 (43.0, 55.0)	13.084	2.917	0.542
FIL	62 (55.0, 97.0)	7.972	2.755	0.63
TEC	89 (76.0, 131.0)	5.977	2.656	0.682
EngI	274 (220.0, 274.0)	1.572	2.158	0.919
ECI	165 (131.0, 220.0)	3.188	2.431	0.794
PRE	43 (43.0, 50.0)	9.949	2.828	0.591
WIN	49 (47.0, 76.0)	12.674	2.907	0.548
NDVI	47 (45.0, 55.0)	10.856	2.857	0.575

Table A3. Monte Carlo test for spatial variability.

Variable	<i>p</i> -Value
Intercept	0.000
POP	0.929
UR	0.957
PCIP	0.882
SecI	0.104
FIL	0.072
TEC	0.010
EngI	0.521
ECI	0.141
PRE	0.000
WIN	0.009
NDVI	0.002

Table A4. Ranking of the importance of influencing factors associated with significant spatial heterogeneity in typical regions.

Region	Variable	ΔR^2
A. The northeastern region	TEC	0.32
	WIN	0.034
	NDVI	0.018
B. The Central Plains	WIN	0.516
	PRE	0.141
	FIL	0.022
C. The Sichuan Basin	FIL	0.306
	SecI	0.249
	NDVI	0.007

Table A4. Cont.

Region	Variable	ΔR^2
D. The Yunnan-Guizhou Plateau	FIL	0.442
	TEC	0.337
	PRE	0.054
	NDVI	0.019
E. The lower reaches of the Yangtze River	NDVI	0.097
	PRE	0.091

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