Article

Assessing Spatial Heterogeneity of Factor Interactions on PM_{2.5} Concentrations in Chinese Cities

Yuhao Jin ¹, Han Zhang ^{2,†} , Hong Shi ³, Huilin Wang ¹, Zhenfeng Wei ⁴, Yuxing Han ^{5,†} and Peitong Cong ^{1,*}

¹ College of Water Conservancy and Civil Engineering, South China Agricultural University, Guangzhou 510642, China; yuhao.jin@scau.edu.cn (Y.J.); whl@scau.edu.cn (H.W.)

² Key Lab of Geographic Information Science of the Ministry of Education, School of Geographic Sciences, East China Normal University, Shanghai 200241, China; zhanghan@geo.ecnu.edu.cn

³ School of Tourism and Historical Culture, Southwest Minzu University, Chengdu 610041, China; shong2021@swun.edu.cn

⁴ College of Economic and Trade, Guangxi University of Finance and Economics, Nanning 530007, China; 2010110009@gxufe.edu.cn

⁵ College of Electronic Engineering, South China Agricultural University, Guangzhou 510642, China; yuxinghan@scau.edu.cn

* Correspondence: slxyky@scau.edu.cn

† The same contributions as the corresponding author.

Abstract: The identification of fine particulate matter (PM_{2.5}) concentrations and its driving factors are crucial for air pollution prevention and control. The factors that influence PM_{2.5} in different regions exhibit significant spatial heterogeneity. Current research has quantified the spatial heterogeneity of single factors but fails to discuss the interactions between factors. In this study, we first divided the study area into subregions based on the spatial heterogeneity of factors in a multi-scale geographically weighted regression model. We then investigated the interactions between different factors in the subregions using the geographical detector model. The results indicate that there was significant spatial heterogeneity in the interactions between the driving factors of PM_{2.5}. The interactions between natural factors have significant uncertainty, as do those between the normalized difference vegetation index (NDVI) and socioeconomic factors. The interactions between socioeconomic factors in the subregions were consistent with those in the whole region. Our findings are expected to deepen the understanding of the mechanisms at play among the aforementioned drivers and aid policymakers in adopting unique governance strategies across different regions.

Keywords: PM_{2.5} concentrations; spatial heterogeneity; multi-scale geographically weighted regression; geographical detector model

Citation: Jin, Y.; Zhang, H.; Shi, H.; Wang, H.; Wei, Z.; Han, Y.; Cong, P. Assessing Spatial Heterogeneity of Factor Interactions on PM_{2.5} Concentrations in Chinese Cities. *Remote Sens.* **2021**, *13*, 5079. <https://doi.org/10.3390/rs13245079>

Academic Editor: Luke Knibbs

Received: 23 October 2021

Accepted: 10 December 2021

Published: 14 December 2021

Publisher's Note: MDPI stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Copyright: © 2021 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

Air quality is deteriorating in many places worldwide and has become a challenge to maintaining human health and driving sustainable development [1]. Socioeconomic development in response to rapid urbanisation has caused serious air pollution problems [2,3], especially the accumulation of fine particulate matter (PM_{2.5}) [4–6]. Despite its low atmospheric content, PM_{2.5} has a crucial impact on air quality and atmospheric visibility [7]. Long- and short-term studies on the relationship between PM_{2.5} and health have confirmed that PM_{2.5} is related to various human health problems [8]. This is because, unlike coarser particles, PM_{2.5}, which has a smaller particle size, can penetrate the human respiratory tract and lungs deeper, increasing the risk of cardiovascular disease and reducing lung function [9]. Prolonged exposure to high PM_{2.5} concentrations, therefore, can increase mortality rates [10]. Given these damaging health impacts, the identification of the key factors and quantification of their effects is vital for alleviating and controlling PM_{2.5}.

It is now understood that PM_{2.5} concentrations are directly affected by human activities and the surrounding environment [11–13]. Previous studies have assessed the

characteristics and sources of $PM_{2.5}$, such as meteorological conditions, transportation, topography, and economic development [14,15]. For example, Zhou et al. [16] found that population density, industrial structure, industrial smoke emissions, and road density tend to have significant positive effects on $PM_{2.5}$. Similarly, Zhu et al. [17] have stated that there is the surge of $PM_{2.5}$ concentration was usually caused by economic activities increase, and there was a unidirectional causality between $PM_{2.5}$ concentration and the factors of economic growth, foreign direct investment, and industrial structure in the long-term. In addition, meteorological factors, such as temperature, air pressure, relative humidity, wind direction, and wind force, can directly or indirectly influence the diffusion degree of $PM_{2.5}$ [18,19]. In fact, $PM_{2.5}$ accumulation is considered to be the synthetic outcome of multivariate natural and social factors, and the interaction between these factors has gradually attracted academic attention. For instance, Yang's study indicated that the interaction between industry and climate is larger than that between ecosystem and climate [20]. Wang et al. [21] also found that the interactions between natural and social factors could enhance the accumulation of $PM_{2.5}$ in a bivariate manner.

To date, a large body of literature has documented the independent and interactive effects of factors on $PM_{2.5}$. Researchers have also noted that the impacts of factors in various regions and development stages have obvious temporal and spatial heterogeneity. For example, Wang et al. [22] investigated spatial heterogeneity in both the direction and strength of socioeconomic and landscape factors at a local scale. Yan et al. [23] observed that the impact of industrial structure on $PM_{2.5}$ concentrations in the upper 75th quantile cities is larger than that in other cities. Moreover, it has been established that the spatial heterogeneity of driving factors increases the difficulty of understanding the accumulation mechanism of $PM_{2.5}$ and poses new challenges for decision-makers to implement interventions. Unfortunately, existing studies have been limited to the evaluation of the spatial heterogeneity of different factors and have ignored the spatial heterogeneity of the interactions between factors. For example, the interaction between temperature and other factors is likely to be different if temperature is found to have an opposite effect on $PM_{2.5}$ in various areas.

Among the various models that are able to quantify the impact of factors on $PM_{2.5}$, such as the spatial regression model, Bayesian hierarchical spatial quantile regression [24], and geographically weighted regression (GWR) [25,26], GWR has been adopted in most studies because it can capture the spatial non-stationarity of geographical phenomena by identifying location-related dynamics [27,28]. Although GWR can analyse the heterogeneity of processes and relationships, its single-core size assumes that each response to the predicted relationship runs on the same spatial scale [29,30]. However, the production of $PM_{2.5}$, which often corresponds to different spatial scales, is actually determined by multiple spatial processes of different scales. Therefore, a multi-scale geographically weighted regression (MGWR) model based on the GWR model has been proposed in previous research, which allows relationships between different variables to run at different spatial scales and captures the impact of spatial scales on different factors by searching for different bandwidths [31]. Additionally, other scholars have noticed the nonlinear interactions between factors and introduced another spatial technique known as the geographical detector (GD) model, as a supplement [16]. Nevertheless, all of these studies have mainly concentrated on the interaction between factors from a global perspective, neglecting spatial heterogeneity in factors.

Based on the shortcomings of previous investigations, this study presents a novel method to quantify the spatial heterogeneity of the interaction between multiple driving factors on $PM_{2.5}$ concentrations. Using cross-sectional data, we first employed the MGWR model to investigate the spatial heterogeneity of the effects of meteorology, topography, and socioeconomic factors on $PM_{2.5}$ concentrations. The study area was then divided into subregions based on the coefficient of the MGWR. Finally, the GD model was used to identify the interactions between driving factors of $PM_{2.5}$ in different subregions. To the best of our knowledge, this is the first study to reveal the spatial heterogeneity of the effects

of interactions between factors on PM_{2.5}. This study can be expected to provide benefits for policymakers and planners to better formulate a PM_{2.5} pollution control scheme.

2. Data and Methods

2.1. Data

2.1.1. PM_{2.5} Concentration Data

For this study, satellite remote sensing and ground monitoring PM_{2.5} data for 2016 was obtained [26]. Compared with most existing PM_{2.5} estimation datasets, our dataset had a higher spatial resolution of 1 km × 1 km. The high-resolution annual average PM_{2.5} concentrations were estimated using the Goddard Earth Observing System chemical (GEOS-Chem) transport model by combining aerosol optical depth (AOD) retrievals from Multi-angle Imaging SpectroRadiometer (MISR), and Sea-viewing Wide Field-of-view Sensor (SeaWiFS) instruments, as well as from the Twin Moderate Resolution Imaging Spectroradiometer (MODIS) instrument [32].

Lu et al. [33] verified satellite data using data from 68 urban monitoring stations in 2013 to determine an R² value of 0.81, and a remotely sensed PM_{2.5} dataset retrieved by van Donkelaar (2016) was found to have good consistency with the ground monitoring data, and thus can be applied to PM_{2.5} research in China [34]. The subset of the global PM_{2.5} concentration dataset covering China was used in this study, and the PM_{2.5} concentration in Chinese cities was calculated based on the spatial statistical analysis method.

2.1.2. Meteorological Data

Meteorological station data were derived from the China Meteorological Administration (<http://data.cma.cn/>) (accessed on 23 October 2021), which records the daily average values of meteorological elements at the stations. To calculate the annual average meteorological data in 2016, we first summed the daily values of average temperature, accumulated precipitation, average air pressure, average wind speed, and average relative humidity, and then averaged the daily meteorological values to annual values [35]. The Partial Thin Plate Smoothing Spline method was used to analyse and interpolate the multivariate data to generate meteorological grid data with a resolution of 1 km, which was suitable for surface fitting and interpolation of meteorological data under the condition of reliable meteorological data and limited data density [36]. Smoothing parameter was used to balance the roughness of the surface and the fidelity of the data, as implemented in the ANUSPLIN package [37]. Moreover, the interpolation surface was smooth and continuous.

2.1.3. Topography Data

The topographical factors selected for this research include elevation (DEM) and the normalized difference vegetation index (NDVI). The dataset known as Advanced Spaceborne Thermal Emission and Reflection Radiometer Global Digital Elevation Model (ASTER GDEM) was used to calculate topological factors, which is a 30 m DEM dataset (<http://www.gscloud.cn/>) (accessed on 23 October 2021). NDVI maintains a significant correlation with PM_{2.5} concentrations [38]. The MODIS NDVI product (MOD13Q1) is a 250 m spatial resolution dataset for 2016 obtained online from the Google Earth Engine (GEE) platform [39,40]. GEE is a cloud platform that combines geospatial and remote sensing satellite images [41,42]. The data stored in GEE include nearly 40 years of historical images and daily updated and expanded datasets, and it has the function of immediate data analysis [43]. The NDVI products were computed from atmospherically corrected bi-directional surface reflectance in GEE platform [44,45]. The annual NDVI in China was obtained by averaging the monthly NDVI data on GEE and downloading it.

2.1.4. Socioeconomic Factors

According to previous studies, human social and economic activities consume energy and increase emissions and atmospheric concentrations of PM_{2.5} [46–49]. Urbanisation, industrial pollution, population growth, vehicle emissions, and other human factors have

far-reaching impacts on PM_{2.5} in different geographical locations [50,51]. Based on existing research results, we selected the following data: areas of built districts (expressed as the proportion of urban built-up area to total area), population density (number of people per unit land area), gross domestic product (GDP), and road density (ratio of total mileage to total area of road network). As shown in Table 1, the aforementioned four socioeconomic factors were derived from the China Statistical Yearbook (CSY) and the China City Statistical Yearbook (CCSY).

Table 1. Data source description.

Category	Factors	Abbreviation	Spatial Resolution	Data Sources
Meteorology	Temperature	TEM	Site-based	Chinese Meteorological Science Data Center (CMDC)
	Precipitation	PRE	Site-based	CMDC
	Air pressure	AP	Site-based	CMDC
	Wind speed	WS	Site-based	CMDC
	Relative humidity	RH	Site-based	CMDC
Topography	Elevation	DEM	30 m	ASTER GDEM
	NDVI	NDVI	250 m	National Aeronautics and Space Administration (NASA)
Social economy	Area of built districts	ABD	Prefecture- level	China Statistical Yearbook (CSY)/China City Statistical Yearbook (CCSY)
	Population density	PD	Prefecture- level	CSY/CCSY
	GDP	GDP	Prefecture- level	CSY/CCSY
	Road density	RD	Prefecture- level	CSY/CCSY

2.2. Multi-Scale Geographically Weighted Regression

The ordinary least squares (OLS) model is a global modelling method which assumes that the parameter estimates of the area are constant [52]. In this model, an equation is used to reflect the overall statistical correlation between the dependent variables and multiple explanatory variables, as follows:

$$y_j = \beta_0 + \sum_{t=1}^p \beta_t x_t + \varepsilon \quad (1)$$

where y_j is the dependent variable, β_0 represents the intercept, β_t is the estimated parameter of the independent variable x_t , p represents the number of impact factors, and ε represents the error term.

The classical GWR considers spatial heterogeneity, but its drawback is that the bandwidth involved is constant throughout the study area; hence, it is not possible to analyse the correlation at different scales or the effect of the local weighted neighbourhood types [53]. This is problematic because different processes in this PM_{2.5} study inevitably involve different spatial scales. Therefore, it is necessary to analyse the local relations under different scales, and the selection of the bandwidth was of great significance for the accurate estimation of local regression model parameters.

The MGWR model improves the defects of GWR, because it uses different bandwidths instead of a single constant bandwidth over the entire study area to determine the geographical relations at different spatial scales [54]. The MGWR model is more convincing than the GWR model because it allows each variable to have its best bandwidth, which can significantly improve the accuracy of the regression analysis. The optimum bandwidths can be found using iterative optimization processes, that either minimizes the corrected Akaike Information Criterion (AICc) or the cross-validation (CV) statistic [31].

$$y_j = \beta_{bw0}(u_j, v_j) + \sum_{t=1}^p \beta_{bw t}(u_j, v_j) x_{jt} + \varepsilon_j \quad (2)$$

where bwt in β_{bwt} indicates the bandwidth used for calibration of the j th relationship. The calibration of the model results in a set of bandwidths, with each variable corresponding to a bandwidth. The difference in bandwidth represents the difference in spatial scale, thus MGWR describes spatial heterogeneity more accurately by capturing the influence of scale in spatial processes.

In order to select the optimal bandwidth for use in the model, the adaptive bi-square kernel function was used. This function eliminates the influence of observations outside the given bandwidth and minimises the Akaike Information Criterion (AIC) and corrected AIC (AICc). Moreover, the performances of the MGWR and OLS models for explaining $PM_{2.5}$ across China were compared using adjusted R^2 values, the residual sum of squares (RSS), AIC, and AICc.

2.3. Geographical Detector Model

The Geographical detector (GD) model is a statistical method to detect spatially stratified heterogeneity and its determinants [14] and has been widely used in studies of land use, ecology, and urban science, among other fields. The GD model assumes that if an independent variable (X) is associated with a dependent variable (Y), they will exhibit a high degree of consistency in their spatial attributes. There are four types of detectors, i.e., factor detector, interaction detector, ecological detector, and risk detector. In this study, factor detectors and interaction detectors were used to detect the impact of variables and their interactions on the $PM_{2.5}$ concentration.

With regard to the factor detector, the GD model employs a q -statistic value to determine the extent to which variable X affects the spatial heterogeneity of variable Y . The q -statistic is calculated as follows:

$$q = 1 - \frac{\sum_{h=1}^L N_h \sigma_h^2}{N \sigma^2} = 1 - \frac{\sum_{h=1}^L N_h \sum_{j=1}^M \left[\frac{(y_h - \bar{y}_h)^2}{N_{hj}} \right]}{N \sigma^2} \quad (3)$$

where $h = 1, 2, \dots, L$ is a certain stratum of the explanatory variable X , L is the number of strata, N represents the number of samples in stratum h or the entire study area, σ_h^2 and σ^2 are the variances of the dependent variable Y in stratum h or the entire study area, respectively, y_h is the risk observation within sub-region h , $\bar{y}_h$ is the mean value of risk observations within sub-region h , and N_{hj} is the number of observations y_h in sub-region h . The q -statistic value is between 0 and 1. The higher the value, the stronger the association between the independent variable X and the dependent variable Y .

The interaction detector can be used to quantify the interactive influence of two explanatory variables ($X1$ and $X2$) and reveals whether the interaction of variables weakens or enhances the influence on Y or whether they are independent in influencing Y . The q -statistic values ($X1$ and $X2$) calculated from the GD model are usually denoted as $q(X1)$ and $q(X2)$, respectively. A new variable layer can be generated by spatially overlaying variable layers $X1$ and $X2$, which can be marked as $X1 \cap X2$. By comparing the q -statistic values of two variables and the q -statistic value of their interaction, five types of interactions can be identified, namely, nonlinear weakened if $q(X1 \cap X2) < \min(q(X1), q(X2))$; univariate weakened if $\min(q(X1), q(X2)) < q(X1 \cap X2) < \max(q(X1), q(X2))$; independent if $q(X1 \cap X2) = q(X1) + q(X2)$; bivariate enhanced if $q(X1 \cap X2) > \max(q(X1), q(X2))$; and nonlinear enhanced if $q(X1 \cap X2) > q(X1) + q(X2)$.

Previous studies have focused on the interactions between factors from a global perspective but ignored the possible heterogeneity of the interactions. Therefore, in this study, the study area was divided into several subregions based on the positive and negative local estimates in the MGWR model, and then the GD model was employed to identify the interaction effects in different subregions.

3. Results

3.1. Spatial Variation Characteristics of PM_{2.5} Concentrations

Figure 1 shows the distribution of PM_{2.5} at a resolution of 1×1 km. The annual average PM_{2.5} concentration in China was $29.47 \mu\text{g}/\text{m}^3$ in 2016. The PM_{2.5} concentration in eastern China was much higher than that in the western region, which showed distinct directivity in the low-altitude plain area. The lowest concentration of PM_{2.5} was found in Changdu of the Tibet autonomous region, with an average value of $3.14 \mu\text{g}/\text{m}^3$. The highest average PM_{2.5} concentration was $81.2 \mu\text{g}/\text{m}^3$, in Hengshui of Hebei Province. According to the air quality guidelines formulated by the World Health Organization (WHO), the WHO Interim target 1 level ($35 \mu\text{g}/\text{m}^3$) is considered the standard limit between low and high PM_{2.5} concentrations. Compared to this value, the results show that nearly half of the cities had higher PM_{2.5} concentrations and were mainly distributed in the North China Plain, Northeast Plain, Sichuan Basin, and Middle-Lower Yangtze plains. It should be noted that all of these regions are densely populated and have rapid economic development. The relatively high PM_{2.5} concentration in the Sichuan Basin is likely closely related to the low terrain and surrounding mountains, which inhibits the diffusion of air pollutants. Likewise, the high concentration in the Northeast Plain is probably due to the presence of heavily polluting industries; however, household heating is also widely conducted in winter.

Figure 1. Spatial distribution of PM_{2.5} concentrations in China.

We adopted the local Moran's I test to further investigate the spatial clustering of PM_{2.5} concentrations in China. The local spatial autocorrelation index (LISA) considers the spatial distance between cities and tests the spatial clustering of PM_{2.5} between neighbouring cities. Figure A1 shows the local spatial autocorrelation results of prefecture-level PM_{2.5} concentrations in China. In general, the areas with high PM_{2.5} concentration were concentrated in the North China Plain and Middle-Lower Yangtze Plain. The low-low cluster refers to the low-value aggregation of PM_{2.5}, and is mainly distributed in the western region, for example, Xinjiang, Tibet, and Qinghai. The lower population density and economic activities in these provinces have resulted in low PM_{2.5} levels. In addition, only a

few cities are distributed in the high-low and low-high clusters, which may be due to the strong spatial diffusion of PM_{2.5}, and the difficulty in isolating high or low values.

3.2. Global Influence of Driving Factors on PM_{2.5} Concentrations

The driving factors of PM_{2.5} include meteorology, topography, and socioeconomic factors. The OLS model was used to determine the impact of nine explanatory variables on prefecture-level PM_{2.5} levels, to elucidate the dominant factors that influence PM_{2.5}. A multicollinearity problem can arise when there is a high degree of correlation between regression variables and the phenomenon of information overlap. Therefore, the linear relationship among the factors was judged by the variance inflation factor (VIF) before analysing the results of the OLS model. As shown in Table 2, multicollinearity did not cause any problems because all the variables related to VIF were below 10, indicating no serious multicollinearity in the model.

Table 2. Global regression results.

Variables	Coefficient	VIF	Variables	Coefficient	VIF
Intercept	7.729 ***	1.046	NDVI	−0.749 *	1.069
TEM	−0.051 ***	1.046	ABD	−0.001 **	2.389
PRE	−0.006 ***	1.102	PD	0.039 ***	1.050
WS	−0.637 ***	1.031	GDP	0.118 ***	2.099
DEM	−0.010 ***	1.128	RD	0.440 ***	1.030

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

The results of the OLS regression suggest that seven explanatory variables were significant at the 1% level. The significance levels of the effects of ABD and NDVI on PM_{2.5} were 5% and 10%, respectively. The coefficient in the OLS model showed that most explanatory variables negatively correlated with PM_{2.5}, including TEM, PRE, WS, DEM, NDVI, and ABD. In contrast, we found that PD and RD had a significant positive effect on PM_{2.5}.

3.3. Spatial Heterogeneity of Influence of Driving Factors

Table 3 shows that the performances of the OLS and MGWR models were significantly different. The AIC and AICc values of the MGWR model were the lowest, indicating a lower difference between the observed value and the fitting value. The highest adjusted R² value of the MGWR model also proves its high fitting degree.

Table 3. Comparison of model performance between the global OLS and the local MGWR models.

Models	R ²	Adjusted R ²	AIC	AICc	RSS
OLS	0.680	0.673	396.235	401.847	92.633
MGWR	0.835	0.829	348.663	356.920	70.215

As shown in Table 4, the influence of cities on PM_{2.5} was significantly different based on MGWR. The values of all driving factors were between positive and negative, indicating that the influence of climate, topology, and socioeconomic variables on the PM_{2.5} concentration has high spatial heterogeneity in China. The spatial distribution of local coefficients is shown in Figures 2 and 3, revealing the high spatial heterogeneity of effects of the driving factors on PM_{2.5} based on the MGWR model.

Table 4. Local estimates of MGWR model.

Variable	Min	Max	Median	Mean	Std	Bandwidth (km)
Intercept	7.274	8.031	7.652	7.691	0.504	12
TEM	−0.295	0.187	−0.063	−0.059	0.061	178
PRE	−0.019	0.005	−0.012	−0.010	0.097	121

Table 4. Cont.

Variable	Min	Max	Median	Mean	Std	Bandwidth (km)
WS	−2.874	1.617	−0.670	−0.652	0.066	163
DEM	−0.037	0.006	−0.014	−0.015	0.011	281
NDVI	−1.892	0.454	−0.801	−0.773	0.212	72
ABD	−0.028	0.017	−0.005	−0.002	0.055	149
PD	−0.010	0.076	0.035	0.031	0.033	230
GDP	−0.561	0.780	0.129	0.122	0.196	87
RD	−0.117	0.962	0.424	0.428	0.117	111

(a) TEM

(b) PRE

(c) WS

(d) DEM

(e) NDVI

Figure 2. Spatial distribution of coefficients for meteorological and topological factors.

Figure 3. Spatial distribution of coefficients for Socioeconomic factors.

Figure 2a–c shows that TEM, PRE, and WS maintained significant effects in all cities. The results show that the temperature rise has an inhibitory effect on the $PM_{2.5}$ concentration in most cities in China, whereas the temperature rise in the northeast and northwest intensifies the influence on the $PM_{2.5}$ concentration. Specifically, the temperature in Tongling had the greatest moderating effect on the concentration of $PM_{2.5}$. In contrast, the temperature in Harbin had the strongest promoting effect on $PM_{2.5}$. In most cities, the impact of precipitation on $PM_{2.5}$ showed a negative correlation. The increase in precipitation along the southeast coast will be accompanied by a decrease in $PM_{2.5}$ concentration. However, the increase in precipitation in the Pearl River Delta will be accompanied by an upward trend in $PM_{2.5}$ concentration. Moreover, wind speed negatively correlated with the $PM_{2.5}$ concentration, as wind action transported pollutants to other areas (Figure 2c). A lower wind speed decreases the diffusion and transportation of fine particles and subsequently increases the concentration of $PM_{2.5}$.

Figure 2d shows a negative correlation between DEM and $PM_{2.5}$ in almost all cities. This suggests that a decrease in DEM enhances the $PM_{2.5}$ concentration. Moreover, the negative correlation between DEM and $PM_{2.5}$ gradually strengthened from western to eastern China. Similarly, as shown in Figure 2e, NDVI and $PM_{2.5}$ concentrations were mainly negatively correlated in southern and western China, which maintained the strongest negative correlation in northern China.

As shown in Figure 3a, ABD negatively correlated with $PM_{2.5}$, and the overall distribution gradually weakened from northwest to southern China. However, a region of positive correlation was observed in the central and coastal areas, but the positive correla-

tion coefficient was relatively small. Figure 3b shows a positive correlation between PD and $PM_{2.5}$ concentrations, indicating that population agglomeration is a dominant factor that influences $PM_{2.5}$. The positive correlation coefficient between population density and $PM_{2.5}$ concentration showed a gradual increase from the south to north, and the northern population density had a greater impact on $PM_{2.5}$.

The regression coefficients of GDP and RD factors are shown in Figure 3c,d. GDP reflects the level of economic output of a region and can therefore be used to measure the degree of regional economic development. Compared with per capita GDP, regional GDP can better reflect regional economic concentration and development levels. The correlation coefficient of GDP in northern China was significantly higher than that in southern China. The GDP in Baoding was found to have the greatest positive effect on $PM_{2.5}$ levels. Moreover, the regression coefficient of road density in eastern China was generally positive, indicating a positive correlation between road area and $PM_{2.5}$. Road density in Suzhou had the greatest enhancement effect on $PM_{2.5}$ concentrations, followed by those in Shanghai and Shaoxing. On the contrary, western China mainly showed negative correlations, which play a significant role in lowering $PM_{2.5}$ concentrations.

Figure 4 illustrates the spatial distribution of the local R^2 values in the MGWR model. The MGWR results showed that the nine driving factors explained 78.50% of the $PM_{2.5}$ concentration distribution. The local R^2 gradually decreased from the north to south, and the MGWR fitting effect was strongest in the northern region. The local R^2 was above 0.75 in Central China and the middle-lower Yangtze River region, which suggests that the influence of climate, topology, and socioeconomic factors on the $PM_{2.5}$ concentration was more significant in this area. The local R^2 of most cities was more than 65.00%, indicating a high goodness of fit in the MGWR model.

Figure 4. Local R^2 values derived from MGWR model.

3.4. Spatial Heterogeneity of Interactions between Driving Factors

Figure 5 depicts the interactions between TEM and other driving factors in different subregions. The interaction effects in the entire region are consistent with those in the TEM(+) region, where the regression coefficient of TEM is positive. In these regions, most q -statistic values are between 0.2 and 0.4, which are higher than those of WS, GDP, and RD but lower than those of PRE, DEM, NDVI, ABD, and PD. Notably, the q -statistic values of TEM decrease significantly in the region where the regression coefficient is negative, that is, the TEM(−) region. The interaction types are nonlinear enhanced in most cases, whereas the interactions between TEM and PRE, ABD, PD, GDP, and RD are bivariate enhanced in the whole region and TEM(+) region.

Figure 5. The q -statistic values of interactions between temperature and other factors derived from the interaction detector. The circle represents the q -statistic value of a single driving factor, the red triangle represents the q -statistic value of the sum

of two driving factors, and the blue triangle is the q -statistic value of the interaction of two driving factors. If the blue triangle is higher than the red one, the interaction type is nonlinearly enhanced; otherwise, it is bivariate enhanced. “All” represents the whole sample. “Factor A(+);Factor B(−)” represents the subregion. For instance, “TEM(+);PRE(+)” is the region of which the coefficients of the TEM and the PRE are both positive.

As shown in Figure 6, although the impact of PRE on PM_{2.5} in most areas is positive, there are differences in the interaction between PRE and TEM and NDVI in the PRE(+) region, in which the interaction between PRE and TEM is bivariate and the interaction between PRE and NDVI is nonlinear enhanced.

Figure 6. The q -statistic values of interactions between precipitation and other factors. The circle represents the q -statistic value of a single driving factor, the red triangle represents the q -statistic value of the sum of two driving factors, and the blue triangle is the q -statistic value of the interaction of two driving factors. If the blue triangle is higher than the red one, the interaction type is nonlinearly enhanced; otherwise, it is bivariate enhanced. “All” represents the whole sample. “Factor A(+);Factor B(−)” represents the subregion.

Figure 7 shows that the influence of WS on $PM_{2.5}$ is consistent in most cases. However, the interaction between WS and ABD is heterogeneous in different subregions. Specifically, the interaction between WS and ABD is nonlinear enhanced in the whole and ABD(−) regions, whereas it is bivariate enhanced in the ABD(+) region.

Figure 7. The q -statistic values of interactions between wind speed and other factors. The circle represents the q -statistic value of a single driving factor, the red triangle represents the q -statistic value of the sum of two driving factors, and the blue triangle is the q -statistic value of the interaction of two driving factors. If the blue triangle is higher than the red one, the interaction type is nonlinearly enhanced; otherwise, it is bivariate enhanced. “All” represents the whole sample. “Factor A(+);Factor B(−)” represents the subregion.

As shown in Figure 8, the interactions between NDVI and PRE, ABD, GDP, and RD are heterogeneous. For instance, in the interaction between NDVI and ABD, the effect of NDVI on $PM_{2.5}$ in the whole region is lower than that of ABD, and both show bivariate enhanced effects. However, the interaction between NDVI and ABD shows nonlinear enhancement in the ABD(+) region, and the q -statistic value of NDVI is higher than that of ABD in the ABD(−) region. In addition, the q -statistic value of NDVI is higher than that of RD in the whole region, but the q -statistic value of RD is higher in the RD(−) region, and the interaction type changes from bivariable enhanced to nonlinear enhanced.

Figure 8. The q -statistic values of interactions between NDVI and other factors. The circle represents the q -statistic value of a single driving factor, the red triangle represents the q -statistic value of the sum of two driving factors, and the blue triangle is the q -statistic value of the interaction of two driving factors. If the blue triangle is higher than the red one, the interaction type is nonlinearly enhanced; otherwise, it is bivariate enhanced. “All” represents the whole sample. “Factor A(+);Factor B(−)” represents the subregion.

In Figure 9, the interactions between GDP and other driving factors indicate that the effect of GDP is higher than that of RD in the whole region but lower in the sub-regions. In addition, the type of interaction between GDP and RD is bivariate enhanced in the RD(−) region, which is also inconsistent with the nonlinear enhancement in the whole region. More interaction results between the driving factors are presented in the Appendix A. Here, we report the interactions with significant heterogeneity, and other results are shown in Appendix A.

Figure 9. The q -statistic values of interactions between GDP and other factors. The circle represents the q -statistic value of a single driving factor, the red triangle represents the q -statistic value of the sum of two driving factors, and the blue triangle is the q -statistic value of the interaction of two driving factors. If the blue triangle is higher than the red one, the interaction type is nonlinearly enhanced; otherwise, it is bivariate enhanced. “All” represents the whole sample. “Factor A(+);Factor B(−)” represents the subregion.

4. Discussion

A better understanding of the spatial heterogeneity among multiple driving factors of PM_{2.5} pollution is beneficial to reveal the different geographical patterns of PM_{2.5} concentrations and help decision-makers and planners formulate PM_{2.5} pollution control strategies. Using the MGWR and GD models, we observed significant spatial heterogeneity not only with respect to the influence of factors, but also with respect to their interactions.

Our results are consistent with previous reports stating that the coefficients in the southeast cities were negative, whilst in the northwest and the northeast, they were found to be positive [55]. Nevertheless, the impact of temperature on PM_{2.5} concentration is still unclear. Generally, the increased temperature can strengthen the atmospheric turbulence and convection that could provide a dynamic field for pollutant transport and spread [56]. However, the temperature can also affect the formation of particles and thus promote the photochemical reaction between precursors [57]. In most cities, the impact of precipitation on PM_{2.5} concentrations showed a negative correlation. This is reasonable because precipitation causes the deposition of pollutants from the atmosphere, and most precipitation processes involve strong convective weather, such as thunderstorms and gales, which have a good removal effect on air pollutants, including PM_{2.5} [58]. Large areal vegetation coverage inferred by high NDVI values is also known to reduce the atmospheric PM_{2.5}, but vegetation typically only plays an auxiliary role in areas dominated by pollution sources and topographical and meteorological factors. However, although farmland typically has a high NDVI value, the PM_{2.5} concentration elevated by dust, straw burning, and fertiliser application. It was further noted that significant spatial changes in the socioeconomic driving factors were also observed. Dense cities and industrial areas are often accompanied by high-density populations, which directly lead to rapid increases in gaseous pollutant emissions in production and living areas, far exceeding the level of natural purification. Compared with that in the south, the impact of human activities on PM_{2.5}, which in this study was more notable in northern China, where thermal power generation and coal-fired heating in winter are prevalent, especially in northeastern China. In addition, the GDP in most cities was found to have a positive effect on PM_{2.5} concentrations, whereas the GDP of only a few cities had a negative impact. This suggests that regional economic development positively impacts PM_{2.5}, which further deteriorates the quality of the atmospheric environment. An obvious feature of our results was the tendency for road density to be the highest in eastern China. This may be because the increase in road density represents the expansion of urban traffic in response to an increase in the number of motor vehicles. Therefore, an increase in exhaust emissions will lead to an increase in atmospheric PM_{2.5}.

For all samples, most interactions between the natural factors nonlinearly enhanced the influences on PM_{2.5} concentrations, except those of the DEM; however, the type of most interactions between socioeconomic factors was bivariate enhanced. This implies that there could be more complicated interactions between natural factors than between socioeconomic factors. For the interactions between natural and socioeconomic factors, most experiments were bivariate enhanced; however, the interactions between WS and PD, GDP, and RD were nonlinearly enhanced. In other words, the impact of socioeconomic development on WS could be vital to explain the PM_{2.5} concentration. Moreover, it can be expected that PD and GDP would affect the height of the city, and the RD would reshape the surface roughness. Compared with those of other related studies (Table 5), our results are more consistent with the results of Wang et al. [21] but are inconsistent with the results of Wu et al. [59]. This could be due to the different sizes of the research units since the larger the size of research units can reduce the spatial heterogeneity that could affect the results of the GD model. Given that the socioeconomic data are typically aggregated at the prefecture level, this study and Wang et al. [21] both adopted Chinese cities, while Wu et al. [59] selected grid cells with a spatial scale of 20 × 20 km. In addition to interactions at the global scale, this study goes one step further. Our results indicate that the interactions have obvious spatial heterogeneity, as do the impacts of driving factors, especially TEM and NDVI. The change in temperature not only affects the urban natural systems (e.g., the

meteorological system) but also the socio-economic systems, such as the energy assumption (e.g., heating). For NDVI, it is generally believed that vegetation can exert adsorption and dust reduction effects to alleviate PM_{2.5} levels. However, the alleviating effect of NDVI could also be related to precipitation and socioeconomic factors.

Table 5. Types of interactions between driving factors in different studies.

	TEM	PRE	WS	DEM	NDVI	ABD	PD	GDP
PRE	1; <u>1</u> ;2	-	-	-	-	-	-	-
WS	2; <u>2</u> ;1	2; <u>2</u> ;1	-	-	-	-	-	-
DEM	2;2	1;2	1;1	-	-	-	-	-
NDVI	2;2	2;1	2;1	1;2	-	-	-	-
ABD	1	1	1	1	1	-	-	-
PD	1; <u>1</u> ;2	1; <u>2</u> ;2	2; <u>2</u> ;2	1;2	1;2	1	-	-
GDP	1;2	1;2	2;1	1;2	1;2	1	1;1	-
RD	1	1	2	1	1	1	1	2

Note: Enhanced, bivariate—1; Nonlinearly enhance—2; 1 and 2 are from [21]; 1 and 2 are from [59].

As mentioned before, previous studies employed the MGWR and GD models to detect the spatial heterogeneity of factors and the interactions between factors from a global perspective. Our contribution is to provide a novel analysis process, that is, to partition the samples according to the heterogeneity of factors and then evaluate the spatial interactions in subregions. Our results highlighted that spatial heterogeneity is not only in factors but also in their interactions. Although the effect of a single driving factor is small, the interaction with other factors could present a higher q-statistic value. For instance, in Figure 5F, the interaction between TEM and PD in the “TEM(−);PD(−)” region shows that the q-statistic value of the interaction is higher than 0.6, however, the q-statistic of the TEM is less than 0.1. Therefore, we cannot control one factor and ignore others, especially the interactions between natural and socioeconomic factors [21].

Our approach has some limitations. The analysis data of urban research did not include all cities in China, which was primarily due to the lack of relevant data for most western cities. Most cities in the MGWR model were concentrated in the eastern and middle parts of the country, with fewer data from western cities. The GD model can only detect interactions between two factors. The identification of the influence of multiple factors could require a couple of process models, such as the atmospheric model, land use change model, and socioeconomic model. Our study mainly quantified the various influences of different factors using statistical methods, and the results may help to establish the process model of PM_{2.5} concentration in the future.

5. Conclusions

Identification of the impacts of factors and their interactions on PM_{2.5} concentrations is crucial for air pollution control and prevention. However, PM_{2.5} concentrations are dependent on numerous factors, and their mechanisms and processes remain unclear. In different regions, the effects of different factors have spatial heterogeneity, which undoubtedly increases the complexity and difficulty of research. In this study, we divided our study area into subregions according to the spatial heterogeneity of factors based on the MGWR model and then employed a GD model to identify the interactions between factors in different subregions. Our findings revealed the spatial heterogeneity of the interactions between the factors for the first time. Specifically, the interactions between natural factors have significant uncertainty, as do the interactions between NDVI and socioeconomic factors. The interactions between socioeconomic factors in the subregions were consistent with those in the entire region. Given the importance to identify factor pairs that exhibit strong interactions between natural factors and socioeconomic factors in managing air pollution [59], the spatial heterogeneity of the interactions suggests that policymakers pay more attention to the subregions with nonlinearly enhanced interactions, while the interaction type is bivariate enhanced in the whole sample [60]. Nonetheless,

our study is at the exploratory stage, and future research should focus on the following aspects: (1) for atmospheric science, it is important to couple the nonlinear interactions between natural factors in $PM_{2.5}$ modelling and verify them in different regions; (2) for social science, researchers should further consider the influence of different policies on socioeconomic factors and interactions with natural factors; (3) scale problems are still key issues, and this would call for more empirical studies to understand the complexity and uncertainty of the target factors; (4) for the data issue, it was not possible to study some geographical region due to a lack of available data. Future research should attempt to incorporate more extensive geographical data for empirical analysis.

Author Contributions: Conceptualization, Y.J. and H.Z.; Data curation, Y.J.; Funding acquisition, Y.H., P.C. and Y.J.; Investigation, Y.J. and H.Z.; Methodology, Y.J. and H.Z.; Resources, Y.H. and P.C.; Supervision, Y.H. and P.C.; Writing—original draft, Y.J. and H.Z.; Writing—review and editing, H.S., H.W. and Z.W. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the National Natural Science Foundation of China (grant no. 42101422 and no. 42001339), and the National Natural Science Foundation of Guangdong Province, China (No. 2018B030306026); Key Fields Special Project of Artificial Intelligence in Guangdong Province (No. 2019KZDZX1001). Project supported by Guangdong Engineering and Research Center for Unmanned Aerial Vehicle Remote Sensing of Agricultural Water and Soil Information.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Acknowledgments: We thank the editor and reviewers for their comments on this paper. Han Zhang, Yuxing Han, and Peitong Cong served as the corresponding author for this article.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A. Local Moran's Test

Figure A1. Local Moran's I clusters of $PM_{2.5}$ concentrations in China.

Figure A2. The q -statistic of interaction between DEM and other factors. The circle represents the q -statistic value of a single driving factor, the red triangle represents the q -statistic value of the sum of two driving factors, and the blue triangle is the q -statistic value of the interaction of two driving factors. If the blue triangle is higher than the red one, the interaction type is nonlinearly enhanced; otherwise, it is bivariate enhanced. “All” represents the whole sample. “Factor A(+);Factor B(−)” represents the subregion.

Figure A3. The q -statistic of interaction between area of built districts (ABD) and other factors. The circle represents the q -statistic value of a single driving factor, the red triangle represents the q -statistic value of the sum of two driving factors, and the blue triangle is the q -statistic value of the interaction of two driving factors. If the blue triangle is higher than the red one, the interaction type is nonlinearly enhanced; otherwise, it is bivariate enhanced. “All” represents the whole sample. “Factor A(+);Factor B(−)” represents the subregion.

Figure A4. The q -statistic of interaction between population density (PD) and other factors. The circle represents the q -statistic value of a single driving factor, the red triangle represents the q -statistic value of the sum of two driving factors, and the blue triangle is the q -statistic value of the interaction of two driving factors. If the blue triangle is higher than the red one, the interaction type is nonlinearly enhanced; otherwise, it is bivariate enhanced. "All" represents the whole sample. "Factor A(+);Factor B(-)" represents the subregion.

Figure A5. The q -statistic of interaction between road density (RD) and other factors. The circle represents the q -statistic value of a single driving factor, the red triangle represents the q -statistic value of the sum of two driving factors, and the blue triangle is the q -statistic value of the interaction of two driving factors. If the blue triangle is higher than the red one, the interaction type is nonlinearly enhanced; otherwise, it is bivariate enhanced. “All” represents the whole sample. “Factor A(+);Factor B(−)” represents the subregion.

References

1. Lelieveld, J.; Evans, J.S.; Fnais, M.; Giannadaki, D.; Pozzer, A. The contribution of outdoor air pollution sources to premature mortality on a global scale. *Nature* **2015**, *525*, 367–371. [\[CrossRef\]](#)
2. Liu, J.; Diamond, J. China's environment in a globalizing world. *Nature* **2005**, *435*, 1179. [\[CrossRef\]](#)
3. Wang, C.; Lin, Z. Environmental Policies in China over the Past 10 Years: Progress, Problems and Prospects. *Procedia Environ. Sci.* **2010**, *2*, 1701–1712.
4. Guo, H.; Cheng, T.; Gu, X.; Wang, Y.; Chen, H.; Bao, F.; Shi, S.; Xu, B.; Wang, W.; Zuo, X. Assessment of PM_{2.5} concentrations and exposure throughout China using ground observations. *Sci. Total Environ.* **2017**, *601–602*, 1024–1030. [\[CrossRef\]](#) [\[PubMed\]](#)
5. Chen, Z.; Cai, J.; Gao, B.; Xu, B.; Dai, S.; He, B.; Xie, X. Detecting the causality influence of individual meteorological factors on local PM_{2.5} concentration in the Jing-Jin-Ji region. *Sci. Rep.* **2017**, *7*, 40735. [\[CrossRef\]](#)
6. Fang, C.; Zhou, C.; Gu, C.; Chen, L.; Li, S. A proposal for the theoretical analysis of the interactive coupled effects between urbanization and the eco-environment in mega-urban agglomerations. *J. Geogr. Sci.* **2017**, *27*, 1431–1449. [\[CrossRef\]](#)
7. Han, X.; Li, H.; Liu, Q.; Liu, F.; Arif, A. Analysis of influential factors on air quality from global and local perspectives in China. *Environ. Pollut.* **2019**, *248*, 965–979. [\[CrossRef\]](#)
8. Nowak, D.J.; Hirabayashi, S.; Bodine, A.; Hoehn, R. Modeled PM_{2.5} removal by trees in ten US cities and associated health effects. *Environ. Pollut.* **2013**, *178*, 395–402. [\[CrossRef\]](#) [\[PubMed\]](#)
9. James Gauderman, W.; McConnell, R.O.B.; Gilliland, F.; London, S.; Thomas, D.; Avol, E.; Vora, H.; Berhane, K.; Rappaport, E.B.; Lurmann, F. Association between air pollution and lung function growth in southern California children. *Am. J. Respir. Crit. Care Med.* **2000**, *162*, 1383–1390. [\[CrossRef\]](#)
10. Hvidtfeldt, U.A.; Sørensen, M.; Geels, C.; Ketzel, M.; Khan, J.; Tjønneland, A.; Overvad, K.; Brandt, J.; Raaschou-Nielsen, O. Long-term residential exposure to PM_{2.5}, PM₁₀, black carbon, NO₂, and ozone and mortality in a Danish cohort. *Environ. Int.* **2019**, *123*, 265–272. [\[CrossRef\]](#) [\[PubMed\]](#)
11. Han, L.; Zhou, W.; Li, W. Increasing impact of urban fine particles (PM 2.5) on areas surrounding Chinese cities. *Sci. Rep.* **2015**, *5*, 12467.
12. Bei, N.; Zhao, L.; Wu, J.; Li, X.; Feng, T.; Li, G. Impacts of sea-land and mountain-valley circulations on the air pollution in Beijing-Tianjin-Hebei (BTH): A case study. *Environ. Pollut.* **2018**, *234*, 429–438. [\[CrossRef\]](#) [\[PubMed\]](#)
13. Yun, G.; Zuo, S.; Dai, S.; Song, X.; Xu, C.; Liao, Y.; Zhao, P.; Chang, W.; Chen, Q.; Li, Y.; et al. Individual and Interactive Influences of Anthropogenic and Ecological Factors on Forest PM_{2.5} Concentrations at an Urban Scale. *Remote Sens.* **2018**, *10*, 521. [\[CrossRef\]](#)
14. Wang, X.; Dickinson, R.E.; Su, L.; Zhou, C.; Wang, K. PM_{2.5} pollution in China and how it has been exacerbated by terrain and meteorological conditions. *Bull. Am. Meteorol. Soc.* **2018**, *99*, 105–119. [\[CrossRef\]](#)
15. Li, P.; Yan, R.; Yu, S.; Wang, S.; Liu, W.; Bao, H. Reinstate regional transport of PM_{2.5} as a major cause of severe haze in Beijing. *Proc. Natl. Acad. Sci. USA* **2015**, *112*, E2739–E2740. [\[CrossRef\]](#)
16. Zhou, C.; Chen, J.; Wang, S. Examining the effects of socioeconomic development on fine particulate matter (PM_{2.5}) in China's cities using spatial regression and the geographical detector technique. *Sci. Total Environ.* **2018**, *619*, 436–445. [\[CrossRef\]](#)
17. Zhu, L.; Hao, Y.; Lu, Z.-N.; Wu, H.; Ran, Q. Do economic activities cause air pollution? Evidence from China's major cities. *Sustain. Cities Soc.* **2019**, *49*, 101593. [\[CrossRef\]](#)
18. Sá, E.; Tchepel, O.; Carvalho, A.; Borrego, C. Meteorological driven changes on air quality over Portugal: A KZ filter application. *Atmos. Pollut. Res.* **2015**, *6*, 979–989. [\[CrossRef\]](#)
19. Calkins, C.; Ge, C.; Wang, J.; Anderson, M.; Yang, K. Effects of meteorological conditions on sulfur dioxide air pollution in the North China plain during winters of 2006–2015. *Atmos. Environ.* **2016**, *147*, 296–309. [\[CrossRef\]](#)
20. Yang, D.; Wang, X.; Xu, J.; Xu, C.; Lu, D.; Ye, C.; Wang, Z.; Bai, L. Quantifying the influence of natural and socioeconomic factors and their interactive impact on PM_{2.5} pollution in China. *Environ. Pollut.* **2018**, *241*, 475–483. [\[CrossRef\]](#)
21. Wang, Y.; Liu, C.; Wang, Q.; Qin, Q.; Ren, H.; Cao, J. Impacts of natural and socioeconomic factors on PM_{2.5} from 2014 to 2017. *J. Environ. Manag.* **2021**, *284*, 112071. [\[CrossRef\]](#) [\[PubMed\]](#)
22. Wang, J.; Wang, S.; Li, S. Examining the spatially varying effects of factors on PM_{2.5} concentrations in Chinese cities using geographically weighted regression modeling. *Environ. Pollut.* **2019**, *248*, 792–803. [\[CrossRef\]](#) [\[PubMed\]](#)
23. Yan, M.; Liu, J.; Wang, Z.; Ning, L. Biogeophysical impacts of land use/land cover change on 20th century anthropogenic climate compared to the impacts of greenhouse gas change. *Int. J. Climatol.* **2020**, *40*, 6560–6573. [\[CrossRef\]](#)
24. Zou, Q.; Shi, J. The heterogeneous effect of socioeconomic driving factors on PM_{2.5} in China's 30 province-level administrative regions: Evidence from Bayesian hierarchical spatial quantile regression. *Environ. Pollut.* **2020**, *264*, 114690. [\[CrossRef\]](#)
25. Gu, K.; Zhou, Y.; Sun, H.; Dong, F.; Zhao, L. Spatial distribution and determinants of PM 2.5 in China's cities: Fresh evidence from IDW and GWR. *Environ. Monit. Assess.* **2021**, *193*, 1–22. [\[CrossRef\]](#)
26. Chen, J.; Zhou, C.; Wang, S.; Hu, J. Identifying the socioeconomic determinants of population exposure to particulate matter (PM_{2.5}) in China using geographically weighted regression modeling. *Environ. Pollut.* **2018**, *241*, 494–503. [\[CrossRef\]](#) [\[PubMed\]](#)
27. Brunson, C.; Fotheringham, A.S.; Charlton, M.E. Geographically weighted regression: A method for exploring spatial nonstationarity. *Geogr. Anal.* **1996**, *28*, 281–298. [\[CrossRef\]](#)
28. Brunson, C.; Fotheringham, S.; Charlton, M. Geographically weighted regression. *J. R. Stat. Soc. Ser. D (Stat.)* **1998**, *47*, 431–443. [\[CrossRef\]](#)

29. Fotheringham, A.S.; Brunson, C.; Charlton, M. *Geographically Weighted Regression: The Analysis of Spatially Varying Relationships*; John Wiley & Sons: Chichester, UK, 2003.
30. Fotheringham, A.S.; Crespo, R.; Yao, J. Geographical and temporal weighted regression (GTWR). *Geogr. Anal.* **2015**, *47*, 431–452. [[CrossRef](#)]
31. Fotheringham, A.S.; Yang, W.; Kang, W. Multiscale Geographically Weighted Regression (MGWR). *Ann. Am. Assoc. Geogr.* **2017**, *107*, 1247–1265. [[CrossRef](#)]
32. Van Donkelaar, A.; Martin, R.V.; Brauer, M.; Hsu, N.C.; Kahn, R.A.; Levy, R.C.; Lyapustin, A.; Sayer, A.M.; Winker, D.M. Global estimates of fine particulate matter using a combined geophysical-statistical method with information from satellites, models, and monitors. *Environ. Sci. Technol.* **2016**, *50*, 3762–3772. [[CrossRef](#)] [[PubMed](#)]
33. Lu, D.; Xu, J.; Yang, D.; Zhao, J. Spatio-temporal variation and influence factors of PM_{2.5} concentrations in China from 1998 to 2014. *Atmos. Pollut. Res.* **2017**, *8*, 1151–1159. [[CrossRef](#)]
34. Leung, D.M.; Tai, A.P.K.; Mickley, L.J.; Moch, J.M.; Donkelaar, A.V.; Shen, L.; Martin, R.V. Synoptic meteorological modes of variability for fine particulate matter (PM_{2.5}) air quality in major metropolitan regions of China. *Atmos. Chem. Phys.* **2018**, *18*, 6733–6748. [[CrossRef](#)]
35. Seo, J.; Park, D.-S.R.; Kim, J.Y.; Youn, D.; Lim, Y.B.; Kim, Y. Effects of meteorology and emissions on urban air quality: A quantitative statistical approach to long-term records (1999–2016) in Seoul, South Korea. *Atmos. Chem. Phys.* **2018**, *18*, 16121–16137. [[CrossRef](#)]
36. Hutchinson, M.F. Interpolation of rainfall data with thin plate smoothing splines. Part I: Two dimensional smoothing of data with short range correlation. *J. Geogr. Inf. Decis. Anal.* **1998**, *2*, 139–151.
37. Hutchinson, M.F.; Xu, T. Anusplin version 4.2 user guide. *Cent. Resour. Environ. Stud. Aust. Natl. Univ. Canberra* **2004**, *54*, 5–13.
38. Wu, C.-D.; Chen, Y.-C.; Pan, W.-C.; Zeng, Y.-T.; Chen, M.-J.; Guo, Y.L.; Lung, S.-C.C. Land-use regression with long-term satellite-based greenness index and culture-specific sources to model PM_{2.5} spatial-temporal variability. *Environ. Pollut.* **2017**, *224*, 148–157. [[CrossRef](#)]
39. Hu, Y.; Dong, Y. An automatic approach for land-change detection and land updates based on integrated NDVI timing analysis and the CVAPS method with GEE support. *ISPRS J. Photogramm. Remote Sens.* **2018**, *146*, 347–359. [[CrossRef](#)]
40. Jia, T.; Zhang, X.; Dong, R. Long-Term Spatial and Temporal Monitoring of Cyanobacteria Blooms Using MODIS on Google Earth Engine: A Case Study in Taihu Lake. *Remote Sens.* **2019**, *11*, 2269. [[CrossRef](#)]
41. Gorelick, N.; Hancher, M.; Dixon, M.; Ilyushchenko, S.; Thau, D.; Moore, R. Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote Sens. Environ.* **2017**, *202*, 18–27. [[CrossRef](#)]
42. Jin, Y.; Liu, X.; Yao, J.; Zhang, X.; Zhang, H. Mapping the annual dynamics of cultivated land in typical area of the Middle-lower Yangtze plain using long time-series of Landsat images based on Google Earth Engine. *Int. J. Remote Sens.* **2020**, *41*, 1625–1644. [[CrossRef](#)]
43. Kumar, L.; Mutanga, O. Google Earth Engine applications since inception: Usage, trends, and potential. *Remote Sens.* **2018**, *10*, 1509. [[CrossRef](#)]
44. Tsai, Y.H.; Stow, D.; Chen, H.L.; Lewison, R.; An, L.; Shi, L. Mapping vegetation and land use types in fanjingshan national nature reserve using google earth engine. *Remote Sens.* **2018**, *10*, 927. [[CrossRef](#)]
45. Jin, Y.; Liu, X.; Chen, Y.; Liang, X. Land-cover mapping using Random Forest classification and incorporating NDVI time-series and texture: A case study of central Shandong. *Int. J. Remote Sens.* **2018**, *39*, 8703–8723. [[CrossRef](#)]
46. Kan, H.; Chen, R.; Tong, S. Ambient air pollution, climate change, and population health in China. *Environ. Int.* **2012**, *42*, 10–19. [[CrossRef](#)]
47. Barker, H.W. Isolating the industrial contribution of PM_{2.5} in Hamilton and Burlington, Ontario. *J. Appl. Meteorol. Climatol.* **2013**, *52*, 660–667. [[CrossRef](#)]
48. Lou, C.-R.; Liu, H.-Y.; Li, Y.-F.; Li, Y.-L. Socioeconomic drivers of PM_{2.5} in the accumulation phase of air pollution episodes in the Yangtze River Delta of China. *Int. J. Environ. Res. Public Health* **2016**, *13*, 928. [[CrossRef](#)]
49. Mataveli, G.A.; Silva, M.E.; França, D.D.; Brunsell, N.A.; de Oliveira, G.; Cardozo, F.D.; Bertani, G.; Pereira, G. Characterization and Trends of Fine Particulate Matter (PM_{2.5}) Fire Emissions in the Brazilian Cerrado during 2002–2017. *Remote Sens.* **2019**, *11*, 2254. [[CrossRef](#)]
50. Gao, L.; Tian, Y.; Zhang, C.; Shi, G.; Hao, H.; Zeng, F.; Shi, C.; Zhang, M.; Feng, Y.; Li, X. Local and long-range transport influences on PM_{2.5} at a cities-cluster in northern China, during summer 2008. *Particuology* **2014**, *13*, 66–72. [[CrossRef](#)]
51. Xu, B.; Lin, B. Regional differences of pollution emissions in China: Contributing factors and mitigation strategies. *J. Clean. Prod.* **2016**, *112*, 1454–1463. [[CrossRef](#)]
52. Hutcheson, G.D. Ordinary least-squares regression. *SAGE Dict. Quant. Manag. Res.* **2011**, 224–228. [[CrossRef](#)]
53. Li, Z.; Fotheringham, A.S.; Oshan, T.M.; Wolf, L.J. Measuring bandwidth uncertainty in multiscale geographically weighted regression using akaike weights. *Ann. Am. Assoc. Geogr.* **2020**, *110*, 1500–1520. [[CrossRef](#)]
54. Oshan, T.M.; Smith, J.P.; Fotheringham, A.S. Targeting the spatial context of obesity determinants via multiscale geographically weighted regression. *Int. J. Health Geogr.* **2020**, *19*, 1–17. [[CrossRef](#)]
55. Liu, Q.; Wu, R.; Zhang, W.; Li, W.; Wang, S. The varying driving forces of PM_{2.5} concentrations in Chinese cities: Insights from a geographically and temporally weighted regression model. *Environ. Int.* **2020**, *145*, 106168. [[CrossRef](#)] [[PubMed](#)]

-
56. Yang, X.; Wang, S.; Zhang, W.; Zhan, D.; Li, J. The impact of anthropogenic emissions and meteorological conditions on the spatial variation of ambient SO₂ concentrations: A panel study of 113 Chinese cities. *Sci. Total Environ.* **2017**, *584–585*, 318–328. [[CrossRef](#)] [[PubMed](#)]
 57. Wang, J.; Ogawa, S. Effects of Meteorological Conditions on PM_{2.5} Concentrations in Nagasaki, Japan. *Int. J. Environ. Res. Public Health* **2015**, *12*, 9089–9101. [[CrossRef](#)]
 58. Wei, L.A.; Yza, B.; Ping, L.C. Numerical simulation of the influence of major meteorological elements on the concentration of air pollutants during rainfall over Sichuan Basin of China. *Atmos. Pollut. Res.* **2020**, *11*, 2036–2048.
 59. Wu, T.; Zhou, L.; Jiang, G.; Meadows, M.E.; Zhang, J.; Pu, L.; Wu, C.; Xie, X. Modelling Spatial Heterogeneity in the Effects of Natural and Socioeconomic Factors, and Their Interactions, on Atmospheric PM_{2.5} Concentrations in China from 2000–2015. *Remote Sens.* **2021**, *13*, 2152. [[CrossRef](#)]
 60. Wu, W.; Zhang, M.; Ding, Y. Exploring the effect of economic and environment factors on PM_{2.5} concentration: A case study of the Beijing-Tianjin-Hebei region. *J. Environ. Manag.* **2020**, *268*, 110703. [[CrossRef](#)]