



Article

The Effect of Urban Form on PM_{2.5} Concentration: Evidence from China's 340 Prefecture-Level Cities

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Abstract: Exploring how urban form affects the Particulate Matter 2.5 (PM_{2.5}) concentration could help to find environmentally friendly urbanization. According to the definition of geography, this paper constructs a comprehensive urban form evaluation index system applicable to many aspects. Four urban form metrics, as well as road density and five control variables are selected. Based on 2015 data on China's 340 prefecture-level cities, the spatial regression model and geographically weighted regression model were used to explore the relationship between the urban form evaluation index system and PM_{2.5} pollution. The main results show that the spatial distribution of PM_{2.5} in China follows an increasing trend from northwest to southeast. Urban form indicators such as AI, LPI, PLAND, LSI and road density were all significantly related to PM_{2.5} concentrations. More compact urban construction, lower fragmentation of urban land, and lower density of the road network are conducive factors for improving air quality conditions. In addition, affected by seasonal changes, the correlation between urban form and PM_{2.5} concentration in spring and winter is higher than that in summer and winter. This study confirmed that a reasonable urban planning strategies are very important for improving air quality.

Keywords: urban form; PM_{2.5}; landscape metrics; geographically weighted regression



Citation: Liu, Y.; He, L.; Qin, W.; Lin, A.; Yang, Y. The Effect of Urban Form on PM_{2.5} Concentration: Evidence from China's 340 Prefecture-Level Cities. *Remote Sens.* **2022**, *14*, 7. <https://doi.org/10.3390/rs14010007>

Academic Editors: Maria João Costa and Daniele Bortoli

Received: 21 October 2021

Accepted: 17 December 2021

Published: 21 December 2021

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1. Introduction

In the past several decades, with the rapid urbanization and industrialization across many regions of the world, atmospheric pollution became increasingly serious and is already a major social problem [1,2]. Especially in China, as the largest developing country, the rate of urbanization increased from 17.9% to 54.8% in years between 1978 and 2015 years and continues to increase [3,4]. The average Particulate Matter 2.5 (PM_{2.5}) concentration in cities reached 62 µg m⁻³, 60.8 µg m⁻³, and 57 µg m⁻³ in 2013, 2014, and 2015, respectively. China became the most PM_{2.5}-polluted area in the world [5]. PM_{2.5} is considered one of the most important pollutants because of its indirect impacts on health, agriculture production, atmospheric visibility, and climate environment [6,7]. In 2001–2006, 165 prefectures' annual PM_{2.5} levels had far and away beyond the national atmosphere quality standard of China (NAQSC, annual average < 35 µg m⁻³) [8]. Many studies showed that PM_{2.5} is a key atmosphere pollutant threatening public health [9,10]. An increase of PM_{2.5} concentration by 10 µg/m³ causes a 0.40% increase in all-course mortality, a 1.43% increase in deaths caused by respiratory failure, and a 0.53% increase in deaths caused by cardiovascular failure [11]. It is estimated that PM_{2.5} pollution caused 1.2 million premature deaths in China in 2010 and nearly 35% of worldwide deaths [12].

To explore the factors that affect PM_{2.5} concentration can help to better analyze the effects of PM_{2.5} pollution. A number of literatures showed that human activities and

natural factors act on $PM_{2.5}$ pollution concentrations either through direct or indirect influences. These influences may be social economy [2,13], the industrial structure [5], climate change [14], seasonality [15], or the prevalence of monsoons [16]. For example, Xu found that economic growth had the large impact on $PM_{2.5}$ [5]. Most studies found a clear reverse “U-shaped” curve between economic development levels, urbanization, and atmosphere pollution, and with improving economy levels, most cities are at a stage of increasing pollution levels [2,17]. It was confirmed that $PM_{2.5}$ pollution is influenced by seasons and regions, and the highest levels were found in winter despite differences in temperature and relative humidity among different regions. He and his colleague applied the global regression model, and found that increased fossil energy consumption leads to an increase in $PM_{2.5}$ concentrations, while elevation, precipitation, temperature, and GDP per capita are all likely to reduce the impact of $PM_{2.5}$ pollution [18].

Moreover, many studies showed that urban planning exert a positive effect on the reduction of $PM_{2.5}$ levels over recent years. Examples for these factors are a reasonable urban form, the moderate reduction of road density, building density, population ratios, and improving green spaces [19]. Of course, there are also studies that used comprehensive indicators in the urbanization process to explore the impact on $PM_{2.5}$, for example, the Liveability and Health Index (LHI) [20]. Urban form, which includes a city area as well as its shape and layout, can be defined as urban land use organization and human activity arrangement [21], and it is usually measured by several landscape indicators of a city. $PM_{2.5}$ pollution is affected by vehicle use, green land, pollutant diffusion, and the heat island effect [22]. Research proved that higher urban compactness and less fragmentation (i.e., the largest patch index (LPI)) can reduce $PM_{2.5}$ pollution in China [23,24]. However, other studies argued that motor vehicles are the main cause of atmospheric pollutants emission in cities, and there is a strong correlation between $PM_{2.5}$ and mortality in the traffic emission [25]; thus, a more compact development alone may still increase local $PM_{2.5}$ concentrations and also cause more population to be affected by $PM_{2.5}$ [26]. In the USA, controlling the population, the level of urbanization, and the mixing of different land cover types were found to be important influencing factors between pollutant levels and atmospheric quality [27,28]. In addition, the distance from the main road, the standard deviation of the building floor, and the average floor are the main urban morphological characteristics that affect the spatial variation of a variety of pollutants [29]. In the above analysis, because of the complexity of socioeconomic and natural conditions, the relationship between urban form and $PM_{2.5}$ may be inconsistent and complex. Scientific urban planning can effectively reduce urban $PM_{2.5}$. Therefore, it is necessary to explore the effect of urban form on $PM_{2.5}$.

Investigating $PM_{2.5}$ concentration is important for research. A large number of experiments used to study the relationship between $PM_{2.5}$ and urban form to identify better approaches for reducing atmosphere pollution. Most studies used linear regression models to analyze the urban form indexes that are related to $PM_{2.5}$ pollution and estimated the coefficient of form indexes in the model [30]. In addition, spatial econometric models and the Environmental Kuznets curve (EKC) hypothesis were used to study the socioeconomic and natural factors on urban atmosphere pollution [13,31]. Most studies mainly obtained urban form data through urban land use data and calculated the urban landscape pattern index to represent specific characteristics of the urban form. Most models selected class area (CA), number of patches (NP), patch density (PD), LPI, area-weighted mean shape index (AWMSI), percentage of landscape (PLAND), aggregation index (AI), landscape shape index (LSI), contiguity index (CONTIG), effective mesh size (MESH), interspersion juxtaposition index (IJI), and other landscape pattern indexes [32,33]. $PM_{2.5}$ data are obtained in three main ways: monitoring real-time data through environmental observation sites, monitoring through experimental instruments, and estimating $PM_{2.5}$ concentrations using atmospheric aerosol optical depth (AOD) data obtained from remote sensing images [34]. The latter can compensate for the shortcomings of experimental technology and ground monitoring sites and provides large-scale and real-time continuous observation data [35]. Although many studies explored the correlation between urban form and $PM_{2.5}$ pollution

at different scales from different-sized cities to urban agglomerations to countries, more specific urban form indicators need to be analyzed in the case of China. For example, there is a lack of variables explaining the effects of local meteorological conditions on the spatial aggregation and dispersion of PM_{2.5} pollution. The geographical conditions of China are complex, and the urban forms of different geographical locations vary greatly; therefore, it is necessary to develop more specific urban form indicators to evaluate the shape of cities from different aspects and to measure the urban forms of China more adequately.

To develop more effective urban development strategies that can alleviate air pollution, as well as integrate the strengths and weaknesses of previous scientific research, this paper assesses the relationship between urban form and PM_{2.5}. For this, multisource data is used to establish an index system of urban form. Estimates of PM_{2.5} concentrations are based on AOD data. Based on 340 prefecture-level cities in China, the linear regression model is applied to study the correlation between urban form and PM_{2.5}. Next, a geographically weighted regression (GWR) model is used to analyze the geographical differentiation of the impact urban form exerts on pollutant emissions. PM_{2.5} concentration data and other natural factors are derived from satellite-derived data. Then, a comprehensive evaluation system of urban form indicators was established by using land use data and road network data. Next, the results of the linear regression method and GWR model between urban form and PM_{2.5} concentration are analyzed. The paper ends with a discussion of the research results and presents relevant policy implications.

2. Data and Methods

2.1. Data Sources

Data were collected on the scale of 340 prefecture-level cities to explore the effect of urban form on PM_{2.5} concentration of this study. Table 1 provides the data framework and variables abbreviations for the study. By reference to other research findings as well as our own experimental results [21,36], this research assumes that the urban form will affect the PM_{2.5} concentration through road density, AI, LPI, PLAND, LSI, population density, per capita GDP, and the proportion of secondary industry. Compared with that of other studies, these indicators are combined from the perspective of urban form and economic development. Then, these eight aspects are combined to quantify urban form indicators. In China, different regions have large climatic differences. Both temperature and precipitation significantly impact atmosphere pollution [37], and therefore, these are used as explanatory variables.

Table 1. Abbreviation summary.

Category	Variable Name	Abbreviation
Independent variable	Fine particles matter	PM _{2.5}
	Aggregation index	AI
	Largest patch index	LPI
	Percentage of landscape	PLAND
	Landscape shape index	LSI
	Road density	RD
Explanatory variable	GDP per capita	PCGDP
	Population density	PD
	Proportion of the secondary industrial output-value	SIP
	Temperature	TEM
	Precipitation	PRE
	Methods	Geographically weighted regression
Ordinary least squares		OLS
Spatial error model		SEM
Spatial lag model		SLM

2.1.1. PM_{2.5} Concentration Data Estimation

Many studies used AOD to estimate the concentration of PM_{2.5} pollution, and many experiments proved a significant correlation between PM_{2.5} levels and satellite-obtained AOD. Therefore, satellite remote sensing AOD is an effective tool for PM_{2.5} pollution monitoring. In this study, MERRA-2 was mainly used to estimate PM_{2.5} levels. The dataset was compiled by NASA's Goddard Earth Science Data and Information Service Center (GESDISC, <https://daac.gsfc.nasa.gov/> (accessed on 10 August 2021)), used an upgraded version of the Goddard Earth Observing System Model, Version 5 (GEOS-5) data assimilation system. The spatial resolution of MERRA2 data is $0.5^\circ \times 0.625^\circ$, and the temporal resolution is daily. Combined with the GEOS-5 model, the annual and monthly averages of near-surface PM_{2.5} concentrations were obtained from the AOD observations in the MERRA-2 data set. For data verification, 200 prefecture-level cities were selected, and their urban pollution point data from the China National Environmental Monitoring Centre were compared to the satellite data. As shown in Figure 1, data verification found a high correlation coefficient ($R^2 = 0.688$) between the PM_{2.5} obtained by satellite and field observations. Thus, satellite data can be used to analyze spatial distribution characteristics. Because of the lack of collection and estimation of nitrate aerosols in the adopted data sources and models, the overall PM_{2.5} value is low (accounting for only 20% of the PM_{2.5} level on severely polluted days), but this was shown to impose little influence on the overall spatial distribution pattern [38].

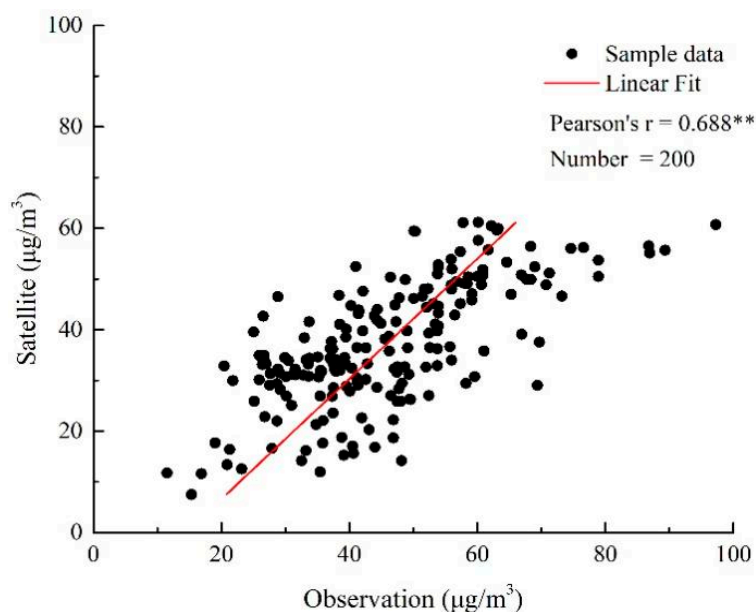


Figure 1. Scatter plot of observation data vs. satellite-retrieved PM_{2.5} data. Note: ** indicate significance levels at 5% levels.

2.1.2. Urban Form Data

Urban form can be defined as the physical characteristics of urban built-up areas, such as their size, shape, and density. Related research on the relationship between urban form and atmospheric quality showed that atmospheric quality is closely related to the fragmentation, size, shape, accessibility, and continuity of the urban form [23]. The landscape patch index is widely used to describe the characteristics of urban land use, as it can scientifically represent the urban form. In the landscape patch of construction land, total built-up area (TA), patch density (PD), mean patch area (MPA), PLAND, LPI, area weighted mean fractal dimension (AWMFD), edge density (ED), LSI, and AI were used to represent the fragmentation, size, shape, accessibility, and continuity of the urban form [39]. Those indices were calculated based on the land use and land cover dataset (1×1 km), obtained by remote sensing classification from Landsat 8 data of 2015.

However, multiple collinearity among these indexes is high. To avoid downstream problems, four indicators were selected based on a variance inflation factor of less than 7.5 [40]. AI indicates the degree of land concentration, and values range within 0–100 (the higher the value, the better the urban land use connectivity). LPI represents the proportion of the maximum patch area to the total land area, with a value range of 0–100 (the higher the value, the lower the city continuity and fragmentation). PLAND is used to measure the size of the area occupied by urban construction land in the whole urban landscape, with a value range of 0–100. LSI indicates the complexity of the shape of a city (the larger the value, the more fragmented urban construction land). These above-mentioned four indicators (i.e., AI, LPI, PLAND, and LSI) represent the expansion of urban construction area, the compactness and fragmentation of construction form, and the complexity of the internal landscape.

In addition, road density is used as a representation of the scale of the urban road network, which is a good measure of urban traffic accessibility. A large amount of traffic increases the concentration of atmosphere pollution, especially in areas next to roads; car exhausts discharge into the atmosphere, and the movement of cars transports dust from the ground into the air, which causes atmospheric pollution [41]. The road network of China was downloaded from OpenStreetMap (<https://www.openstreetmap.org/> (accessed on 10 August 2021)) and computed through ArcGIS 10.x platform. Table 2 provides the calculation method and simple description of 5 urban form indexes.

Table 2. Main urban form indexes in this study.

Index	Formula	Description
Aggregation index	$AI = \left[\frac{g_{ii}}{\max g_{ii}} \right] \times 100$	Measure of the natural connectivity of urban construction land
Largest patch index	$LPI = \frac{\max_i^j (a_{ij})}{TA} (100)$	Measure of the superiority of urban construction land landscape
Percentage of landscape	$PLAND = p_t = \frac{\sum_{j=1}^n a_{mn}}{P} \times 100$	Measure of the proportion of urban construction land in the entire urban landscape
Landscape shape index	$LSI = \frac{0.25 \sum_{k=1}^m e_{ik}^*}{\sqrt{TA}}$	Measure of the fragmentation and complexity of urban construction land
Road density	$RD = \frac{(\text{length})km}{(\text{area})km^2}$	Measure the ratio of road length to area in city

2.1.3. Control Variables

The level of air pollution emissions was influenced by many variables indirectly related to urban form. Therefore, it is necessary to employ a more accurate statistical assessment of the association between urban form and air pollution using control variables.

As socioeconomic data, this paper mainly selects GDP per capita, population density, and the secondary industry proportion (SIP). GDP per capita refers to the economic development of a city. Economic development is the ultimate goal of urban development. According to the EKC, China's economy is ahead of the EKC peak; thus, economic development causes more energy consumption and construction activities, which may be the main source of urban PM_{2.5} pollution [42]. Population density is defined as the number of people per unit of land area, and a significant correlation between population density and atmospheric pollution was found [22]. This paper mainly adopts the population density of urban built-up areas, which is an important indicator of the current status of urban population distribution. SIP refers to the proportion of the output value of the secondary industry within the total industrial output value, which is an important source of urban atmospheric pollutants. The secondary industry encompasses many energy-intensive industries, mainly fossil-fuel power plants, steel mills, cement plants, and chemical plants [2]. The Overall Energy Balance Sheet for National Bureau of Statistics showed that nearly 70% of China's energy consumption is concentrated in the secondary industry. Therefore, compared with that of other industries, the secondary industry emits more atmospheric pollutants [43].

The data of these three indicators all originate from the “China City Statistical Yearbook” of 2015, where missing and partially imputed data were replaced with relevant data from adjacent years (which was the case in 1.5% of the sample).

As natural factors, temperature (TEM) and precipitation (PRE) were selected to measure the city’s climatic characteristics. Meteorological factors play an important role in the concentrations of PM_{2.5} in China (more precipitation and the lower the temperature, the lower the concentration of pollutants) [37]. Latitude and longitude grid data of China were extracted from the acquired MERRA-2 data set, and interpolation processing and regional statistics at 340 prefecture-level cities were performed in the ArcGIS 10.2 software.

2.2. Statistical Models

China has obvious characteristics of regional differentiation, and atmosphere pollution also presents typical regional characteristics. Air pollution between regions has a strong spatial correlation; thus, the air pollution concentration of a city will affect the air quality of nearby cities.

As typical global linear regression model, the ordinary least squares (OLS) model is a common method to quantify the statistical relationship between independent and dependent variables. OLS can be used to study the correlation between urban form and PM_{2.5}. However, the OLS model ignores the influence of spatial heterogeneity, which may lead to evaluation bias [39]. Because of the existing spatial correlation among influencing factors, several spatial regression models were selected to solve the problem by controlling these potential spatial correlations. This paper used the spatial lag model (SLM) and the spatial error model (SEM). SLM explains the influence of variables of the surrounding area by adding lag variables to the model, while SEM considers the spatial dependence of dependent variables (that may otherwise be missed) by adding error terms to the model. The OLS model can be described as:

$$S = \beta_n + \sum_{m=1}^p \beta_m \alpha_m + \varepsilon \quad (1)$$

where S is the dependent variable, β_n is the intercept, β_m is the regression coefficient corresponding to the explanatory variable m , and ε is the random error value. This model can represent the intensity of the relationship between PM_{2.5} and urban form indicators.

The SLM model can be expressed as:

$$y = \beta_0 + \mu \sum_{i=1}^p W_i y + \sum_{i=1}^p \beta_i x_i + \varepsilon \quad (2)$$

where μ is the regression coefficient of the spatial lag term, representing the influencing degree of adjacent spatial units on the spatial unit. This value has certain directivity, and the larger the spatial influence degree, the greater the spatial influence degree. W is the spatial weight matrix of $n \times n$, and W_i is the spatial lag dependent variable of the spatial weight matrix W . The parameter β mainly reflects the influence of the independent variable on the dependent variable and the effect of spatial distance on each spatial unit. In this model, inverse distance was used as the weight of the spatial lag term.

The SEM model can be represented as follows:

$$y = \beta_0 + \sum_{i=1}^p \beta_i x_i + \omega \sum_{i=1}^p W'_i \varepsilon \quad (3)$$

where y is the dependent variable. W is the spatial weight matrix, where the inverse distance was used to calculate the spatial error matrix. β_0 is a normal distributed random error vector. Parameter β_i is the influence coefficient of independent variable x on dependent variable y , and W'_i is the spatial error coefficient of the dependent variable vector, which represents the spatial autocorrelation of the spatial error.

All results of the three regression models can be used to explain the relationship between dependent and independent variables, and the statistical results can be compared by the measurement coefficient (R^2) and Akaike information criterion (AIC) in the model. Both values can be measured relative to a model that is more suitable for this paper. The higher the R^2 value, the smaller the AIC value, indicating that the model is more suitable. All calculation procedures are conducted in Geoda 2017 software.

2.3. Geographically Weighted Regression

In this study, atmospheric pollution presents typical regional characteristics. In other words, the air quality between neighboring cities is geographically closely related. Regression analysis assumes that the regression parameters have no relationship with the geographic location of the sample data, and the spatial characteristics are not considered. The research results do not reflect geographic location characteristics well. In addition, as a spatial autocorrelation index, the results of the bivariate Moran index of $PM_{2.5}$ and 10 indicators are statistically significant (e.g., LPI, AI, and PLAND) and have obvious spatial autocorrelation.

To identify the influence of spatial location, GWR is used to assess the influence of urban morphology of different regions on $PM_{2.5}$ concentration. GWR is an extension of the OLS linear regression model. It uses local regression, embeds spatial position information of the data into the regression parameters, establishes the local weight of the spatial position matrix, and estimates the regression parameters point by point through the local weighted least squares method, to quantify spatial heterogeneity. The model construction is expressed as follows:

$$y_i = \beta_0(u_i, v_i) + \sum_{z=1}^n \beta_z(u_i, v_i)x_{iz} + \varepsilon_i \quad (4)$$

where the dependent variable y_i represents the $PM_{2.5}$ concentration of city i , $\beta_0(u_i, v_i)$ represents the constant term of city i , x_{iz} represents the explanatory variable, $\beta_z(u_i, v_i)$ represents the regression parameter of the independent variable at the data sampling point, and ε_i represents the accumulation error term.

The parameter $\beta_f(u_i, v_i)$ can be estimated by the following formula:

$$\beta_f(u_i, v_i) = \left(X^T W(u_i, v_i) X \right)^{-1} X^T W(u_i, v_i) y \quad (5)$$

where $\beta_f(u_i, v_i)$ is the parameter estimation value of (u_i, v_i) , $W(u_i, v_i)$ is an $n \times n$ spatial weight matrix, the nondiagonal original element value of which is 0, and the diagonal element data is the spatial weight of the observation data of city i . The choice of the spatial weight function is the core of GWR model estimation, and directly determines the correctness of the model parameter estimation. To avoid estimation error caused by less sample data around individual sampling points, this model uses the Gaussian kernel function as the spatial weight function:

$$W_{ij} = \begin{cases} \left[1 - (d_{si}/d_{max})^2 \right]^2 & d_{si} \leq d_{max} \\ 0 & otherwise \end{cases} \quad (6)$$

where d_{si} represents the distance between sampling points s and i , and d_{max} represents the maximum distance between neighboring cities and the city to be assessed.

For the GWR model, bandwidth is important for determining the spatial weight calculation scheme. The smoothness of the model is controlled by bandwidth. Different spatial weighting functions are used to obtain different bandwidths. Fotheringham proposed how to obtain the optimal bandwidth [44]. The standard is the best bandwidth when the AIC of the GWR model is smallest. Therefore, AIC is used to determine the bandwidth.

The formula of the AIC is shown in the following:

$$AIC = -2\ln L(\hat{\theta}_L, x) + 2q \quad (7)$$

where $L(\hat{\theta}_L, x)$ is the likelihood function of the model, $\hat{\theta}_L$ is the maximum likelihood estimation of θ , x is a random sample, and q is the number of unknown parameters. The GWR tool in ArcGIS 10.2 was used to build the model.

3. Results

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

Figure 2 illustrates the geographic distribution of the average $PM_{2.5}$ concentrations of China's cities in 2015, clearly indicating that the spatial distribution of $PM_{2.5}$ is heterogeneous. Overall, cities in eastern China tend to have higher $PM_{2.5}$ levels than cities in western China, and cities in northern China have higher $PM_{2.5}$ levels than cities in southern China. Specifically, areas with highest $PM_{2.5}$ levels are concentrated in the North China Plain and Sichuan Basin, as well as in parts of the Northwest China. Among these, the high $PM_{2.5}$ level-area of the northwest region is mainly caused by the Taklamakan desert (the world's second largest desert), where perennial wind and sand influx causes extremely rich suspended particulate matter; therefore, the concentration of $PM_{2.5}$ in the desert area is high. The level of economic development in the North China Plains is high. The development of pollution-intensive industries in North China promotes regional economic development, and therefore, man-made atmospheric pollutant emissions are very large. In the southwest region, area with high $PM_{2.5}$ pollution is mainly concentrated in the Sichuan Basin, a region that is particularly affected by humidity and precipitation, which causes rich suspended particles in the atmosphere. Moreover, the special structure of the terrain is not conducive to the spread of pollutants, and the population of the region causes high levels of anthropogenic pollution emissions. Because of its elevation, the Qinghai-Tibet Plateau has a thin atmosphere, these conditions are not conducive for the formation and accumulation of particulate matter in the atmosphere. Therefore, the lowest $PM_{2.5}$ levels were found in the Qinghai-Tibet Plateau. The global Moran's I index for $PM_{2.5}$ levels were 0.765 ($p < 0.01$), indicating a relatively strong positive spatial correlation. Local indicators on $PM_{2.5}$ spatial association (LISA) maps show similar typical distributions, with a high $PM_{2.5}$ cluster in the North China Plains and a low $PM_{2.5}$ cluster in the Northeast China and the Qinghai-Tibet Plateau regions (Figure 3). Seasonally, winter had the highest $PM_{2.5}$ level, followed by spring, autumn, and summer. However, North China has always been a region with severe $PM_{2.5}$ pollution, especially in winter, where the climate is not conducive to the diffusion of atmospheric pollutants [45]. On a seasonal scale, winter had the highest $PM_{2.5}$ level, followed by spring, autumn, and summer. However, North China was always a region with severe $PM_{2.5}$ pollution, especially in winter, where the climate is not conducive to the diffusion of atmospheric pollutants. It is worth noting that Southern China always had low $PM_{2.5}$ pollution because of its advantageous climate (Figure 4).

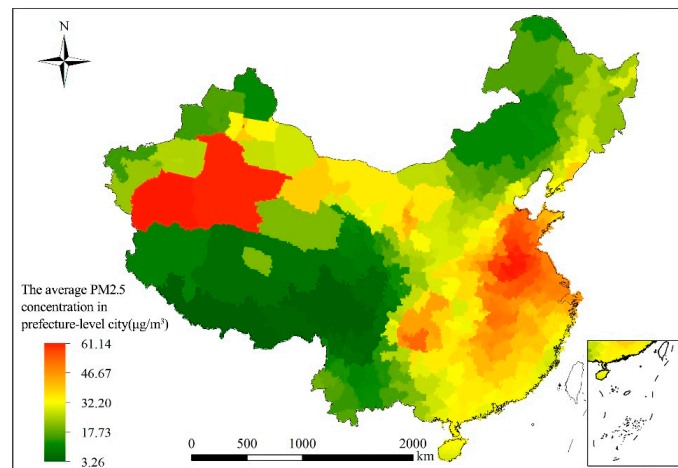


Figure 2. Spatial distribution of PM_{2.5} levels at prefecture-city level in China.

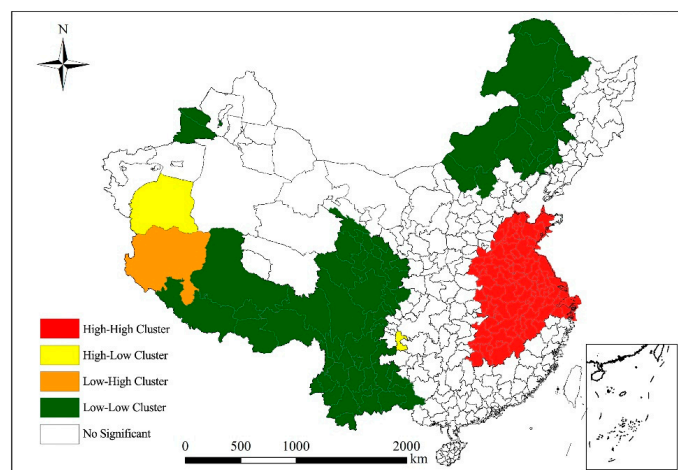


Figure 3. Local indicators on PM_{2.5} spatial association (or LISA) maps of prefecture-level cities in China.

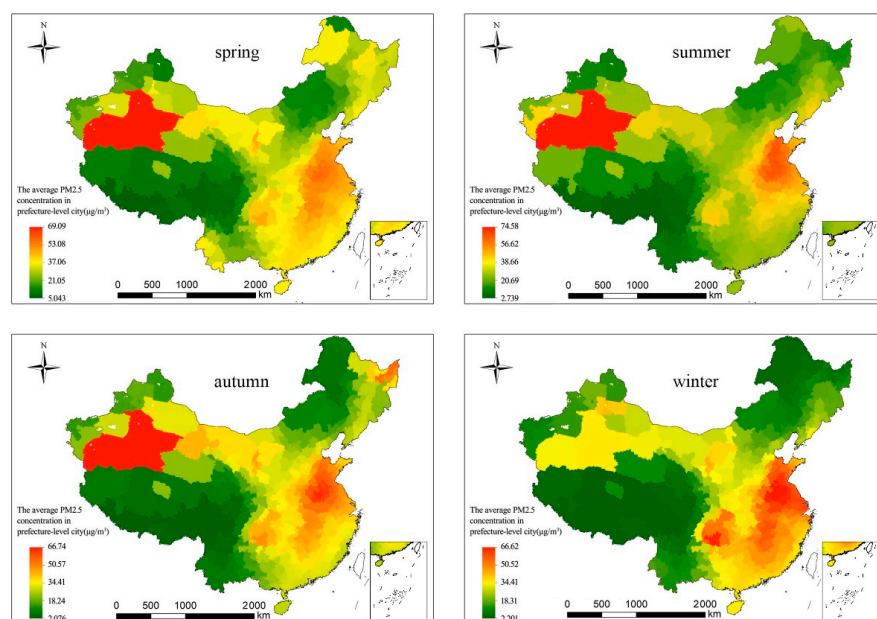


Figure 4. Spatio-temporal distribution of PM_{2.5} levels of prefecture-level cities in spring, summer, autumn, and winter.

3.2. Correlations between Urban Form and PM_{2.5}

Table 3 shows the results of global regression model analysis (i.e., OLS, SLM, and SEM). The results of suitability statistics such as R², AIC, and log-likelihood imply that the spatial analysis technique is more suitable for this data. R² values of OLS, SLM, and SEM models are 0.601, 0.943, and 0.874, respectively. These results show that the spatial effect is important in regression analysis and thus, ignoring the spatial effect will reduce the effectiveness of the model. In addition, R², AIC, and log-likelihood test results show that the spatial lag effect is more significant.

Table 3. Global regression results.

Variable	Classic OLS Model		Spatial Lag Model		Spatial Error Model	
	Coefficient	t-Statistic	Coefficient	z-Value	Coefficient	z-Value
LPI	−1.209 ***	−4.652	−0.075 **	−0.620	−0.327 **	−2.241
AI	0.076	1.202	0.068 ***	2.826	0.0424	1.214
PLAND	0.861 ***	5.298	−0.062 **	−0.753	0.226 **	2.454
LSI	0.226 ***	2.664	0.018 **	0.520	0.034 **	0.722
SIP	0.095 *	1.875	−0.006	−0.263	−0.019	−0.661
PRGDP	2.99 × 10 ⁷	0.013	−1.64 × 10 ⁶	−0.174	1.55 × 10 ⁵	1.176
PD	0.0004	0.430	−0.0002	−0.492	0.0003	0.694
TEM	1.737 ***	12.340	2.878 ***	17.104	0.646 ***	6.369
PER	−2.341 ***	−4.759	−2.038 **	−2.397	−1.013 ***	−3.542
RD	−0.191	−0.129	−0.214	−0.320	−1.005	−1.223

Note: ***, **, or * indicate significance levels at the 1%, 5%, and 10% levels, respectively. OLS model: R²: 0.601, Log likelihood: −1224.72, *p*-value: 0.000; AIC: 2471.45. SLM: R-squared: 0.943, Log likelihood: −954.714, *p*-value: 0.000, AIC: 1931.43. SEM: R-squared: 0.874, Log likelihood: −1057.64; *p*-value: 0.000, AIC: 2139.28.

The results of OLS indicate that most urban form indicators are significantly correlated with PM_{2.5} concentrations, and six urban form indicators showed significantly (*p* < 0.01) positive relationships with city-level annual mean PM_{2.5} levels. Among these six significant factors, LPI, PLAND, and LSI also have a significant impact. LPI has a significant negative correlation with PM_{2.5} levels, indicating that a better continuity of the urban form leads to a lower fragmentation, and a better atmospheric quality. PLAND and LSI were significantly positively correlated with PM_{2.5} levels, indicating that the more complex the urban form, the worse the atmospheric quality. AI indicators on PM_{2.5} concentration is not significant. The four landscape pattern indicators indicate that the fragmentation and complexity of the urban form exert a significant impact on PM_{2.5} levels, and thus, more attention should be focused on urban form area expansion and the internal composition of fragmentation and complexity. RD is negatively correlated with PM_{2.5} levels, and the higher the density of the road network, the lower the atmospheric pollution levels. In addition, there is a significant negative correlation between temperature and precipitation and PM_{2.5} pollution, which confirms that meteorological conditions are conducive to the spread and reduction of atmospheric pollutants. Among other control indicators, SIP has a significantly positive impact on PM_{2.5} pollution, and PD and PRGDP are positively correlated with PM_{2.5} levels. Therefore, the development of the secondary industry has a more significant impact on atmospheric pollution.

The SLM model has the best regression results, indicating that urban form and atmospheric pollution have clear spatial dependence. Among the major urban form indicators, LPI was significantly negatively correlated with PM_{2.5} levels, AI, PLAND, and LSI were significantly positively correlated with PM_{2.5} pollution, and RD was negatively correlated with PM_{2.5} levels. In addition, the correlation between temperature and precipitation on PM_{2.5} was significant (the more precipitation, the lower the temperature), which is beneficial for reducing PM_{2.5} concentrations in the atmosphere. This is consistent with literature. Therefore, clear spatial correlation exists between urban form indicators and PM_{2.5} levels.

the analysis process of the global regression model analysis has limitations. The GWR model can be used for further analysis by adding the relationship of spatial location.

3.3. Spatial Features of Urban Form on $PM_{2.5}$

The coefficient of determination of the GWR model was 0.77, and the results of AIC and variance analysis (F test) showed that the results of the model are statistically significant. All 10 variables show noncollinearity and are used under the AIC minimization standard. The GWR model is superior to the OLS model. Figure 5 shows a distribution map of the regression fitting coefficient R^2 in the regression results for prefecture-level cities. The spatial distribution of R^2 shows that the fitting results of the 10 variables of the urban form range between 0.43 and 0.83, indicating that the 10 indicators selected in this paper exert a stronger comprehensive impact on urban $PM_{2.5}$ levels. Moreover, the R^2 value in the spatial distribution decreases from north to south. Therefore, the urban form system has a stronger explanatory power for the urban form of the northern region. On the one hand, this paper uses temperature and precipitation as control variables of two natural factors. They exert a significant positive effect on reducing atmospheric pollutants. The role of climatic factors is more significant in the south, thus reducing the concentration of urban $PM_{2.5}$ pollution. On the other hand, this may be due to a lack of estimation of nitrate levels in the $PM_{2.5}$ data used in this paper, and therefore, the impact of using a large amount of coal for heating in winter in northern regions may be underestimated, resulting in a low degree of fitting for northern regions. The further south a city is located, the more the explanatory power for $PM_{2.5}$ of the urban form decreases.

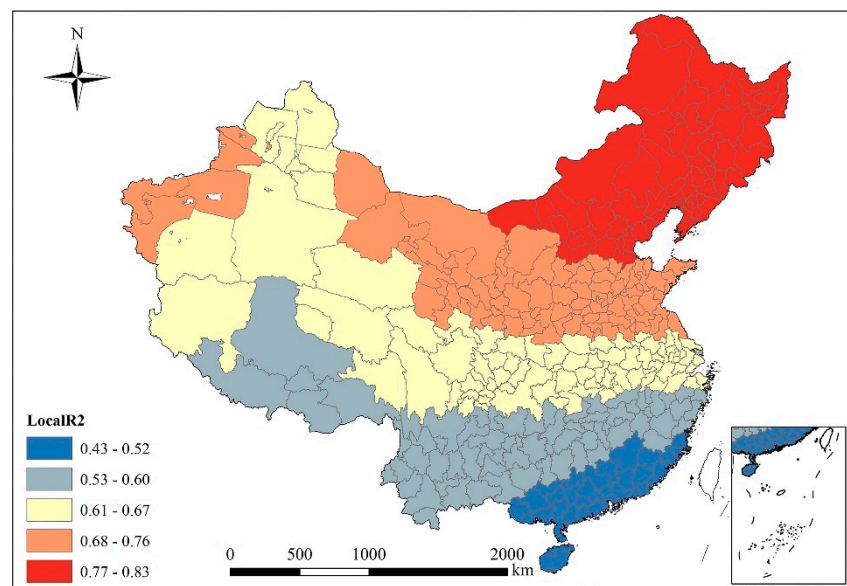


Figure 5. Local R^2 distribution characteristics according to geographically weighted regression (GWR) model.

In the GWR model, each urban form index has a specific regression coefficient for the influence degree of $PM_{2.5}$ levels, and each coefficient has a different spatial distribution law (Figure 6). The spatial distribution can more intuitively depict the influencing effect and changing trend between different urban form indicators and cities. In addition, different indicators exert different positive and negative impacts on $PM_{2.5}$ levels, and their proportions differ. This also indicates that the influence index is not spatially stable and shows spatial heterogeneity (Figure 5). The directions of significant relationships were not the same for the studied cities, even for the same factor.

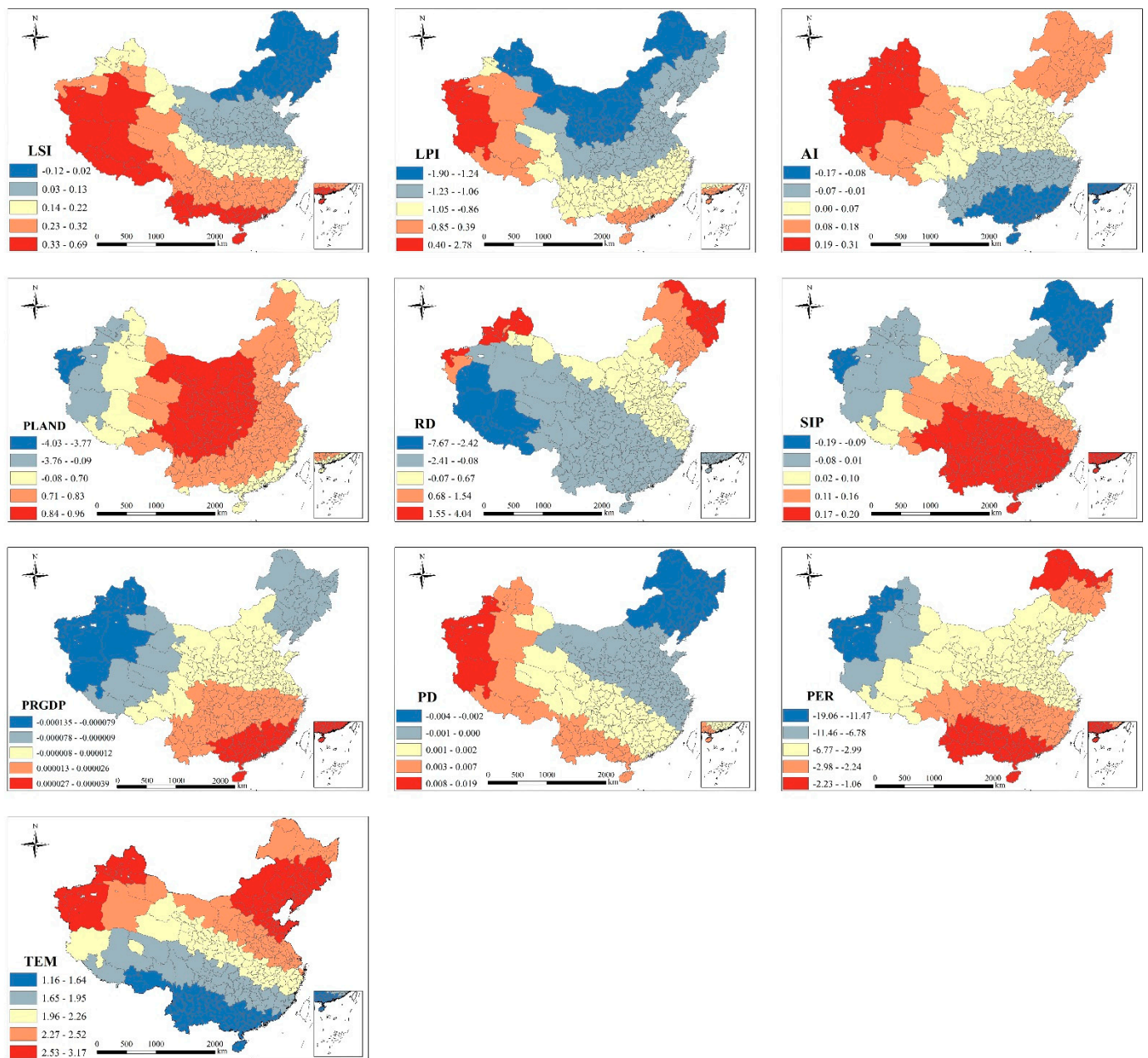


Figure 6. Spatial distribution of local relationship between $PM_{2.5}$ and 10 factors for prefecture-level cities in China.

The regression coefficient of urban form index decreases in the order of RD, PLAND, LPI, LSI, and AI. The correlation between road density and $PM_{2.5}$ levels is highest. Construction dust from the construction phase of roads is the main cause of $PM_{2.5}$ pollution, followed by pollution caused by motor vehicle driving, as well as more harmful gases that are discharged during traffic congestions. The regression coefficient ranges from 7.7 to 4.0 and decreases from northeast to southwest. In China's major urban areas, the density of road networks is negatively correlated with $PM_{2.5}$ concentrations. Improvement of the road network system can effectively reduce traffic congestions and atmospheric pollution. The correlation coefficient between PLAND and $PM_{2.5}$ concentrations is high and negative. This coefficient mainly measures the size of the area occupied by urban construction land in the whole urban landscape. The influencing factor follows a decreasing trend from center to surrounding areas. Cities where construction land is the main land use type are more likely to cause atmospheric pollution. Developed areas in the south are less affected but may be

affected by increasing levels of urban construction, where the application of scientific dust reduction measures and the use of green materials are conducive for reducing emissions of atmospheric pollutants such as building dust. Cities in part of the central and western regions are more susceptible to the impact of the area of construction land. Therefore, reasonable increases of urban construction area and improvement of the level of building construction technology (e.g., green building materials and dust reduction) can reduce $PM_{2.5}$ concentrations to a certain extent. LPI exerts a significant influence on urban $PM_{2.5}$ concentrations, where a continuous increase of LPI indicates that the landscape dominance of urban construction land increases, the degree of spatial connection increases, and the intensity of human activities also increases. The values range from -1.9 to 2.8 and increase from north to south with the continuous development of urban construction, which causes more atmospheric pollution. In southern China, driven by the reform and opening up policy, the urbanization level grows faster, and human activities are more intense. This indicates that enhancing the connectivity and dominance of urban construction land has a significant impact on reducing $PM_{2.5}$ concentrations. A higher LSI index indicates stronger fragmentation and more complicated urban areas. Most regression coefficients between LSI and $PM_{2.5}$ concentrations are positive, with values ranging from -0.12 to 0.69 , indicating that a higher LSI value represents higher levels of $PM_{2.5}$ pollution. The spatial increase from north to south may be due to the complexity and fragmentation of the shape of the landscape of urban construction land, which leads to an increase of people's daily commuting time and distance, thus also increasing the pollution caused by the heavy use of commuting means. The impact degree of the southern region is large, indicating that the complexity of urban landscape in the southern region is more likely to affect the $PM_{2.5}$ levels. AI is used to measure the agglomeration and compactness of urban construction land. The regression coefficient ranges from -0.17 to 0.31 , and it changes from negative to positive from north to south. The higher the compactness of urban construction land, the lower the $PM_{2.5}$ concentrations. Compact urban construction can shorten people's travel distance, improve the efficiency of land use, and reduce energy consumption. Therefore, in the process of urban development, compact and continuous urban construction is conducive to the improvement of urban atmospheric quality.

Among control indicators, the influences of the three socioeconomic factors on urban $PM_{2.5}$ pollution show clear spatial differences. In most urban areas, SIP has a significant positive effect on $PM_{2.5}$ concentrations, indicating that industrial activities aggravate the $PM_{2.5}$ concentrations in Chinese cities, which is consistent with the literature. The effect of SIP on $PM_{2.5}$ concentrations in southern China is strong, indicating that reducing the proportion of output of the secondary industry in southern China can significantly improve atmospheric quality. At the same time, the population density in the southeast coastal areas exerts a greater impact on the $PM_{2.5}$ concentrations. Economic development prompted the migration of many people to the south to work or live. The increased population density has caused more man-made atmospheric pollutant emissions, which strongly impact atmospheric pollution. The overall coefficient of PCGDP is low and its influence is weak. However, in the process of urban development, the improvement of the economic level exerts a significant positive effect on reducing $PM_{2.5}$ pollution levels.

Reasonable increases in the area of urban construction land and improvements of the level of construction, reducing the fragmentation of urban construction land, compacting urban construction, improving traffic accessibility, applying a reasonable road network density are all very beneficial factors for the improvement of urban atmospheric quality. These can, to a certain extent, reduce the concentration of $PM_{2.5}$. However, as urbanization continues to increase, the different geographical location, scale and level of construction, and development of the city should be considered according to local conditions, thus providing planning and construction guidance. Urban form can affect $PM_{2.5}$ concentrations from different aspects. Urban area, geographical location, and economic development level have an impact, and thus also need further discussion and analysis in the future.

4. Discussion

On an annual scale, urban planning factors (e.g., the area of urban construction land, construction fragmentation, and road network density) all exert a specific influence on PM_{2.5} levels. At the same time, the economic development of a city is also closely related to PM_{2.5} levels. China's rapid urbanization led to structural changes of its economy, and large areas of land are being used by energy-intensive and labor-intensive industries. In addition, many people move from rural areas to cities, where the population grows rapidly, which increases the release of large amounts of man-made atmospheric pollutants emission. The study showed that temperature and precipitation (as control variables) were significantly correlated with PM_{2.5} concentrations in 340 cities in China, and climatic factors played a significant role for reducing atmosphere pollution. Therefore, we further discussed this paper discusses the relationship between urban form and PM_{2.5} in different seasons. Seasonality can affect atmospheric quality through changes in precipitation, wind, relative humidity, monsoons, and other diffusion conditions [16,30]. When seasonal variations are considered, different seasons exert different impacts on PM_{2.5} through different urban form indicators. The SLM model achieved the best regression results, and the relationship between urban form and PM_{2.5} in different seasons is discussed through this model (Table 4).

Table 4. Spatial lag model results for different seasons in China during 2015.

Variable	Spring	Summer	Autumn	Winter
LPI	−0.289 ** (−2.044)	−0.489 *** (−3.751)	−0.231 (−1.522)	−0.258 * (−1.775)
AI	0.054 (1.581)	0.0524 * (1.681)	0.044 (1.219)	0.027 (−0.773)
PLAND	0.243 *** (2.793)	0.320 *** (3.943)	0.133 (1.382)	0.240 *** (−2.652)
LSI	0.055 (1.210)	−0.050 (−1.144)	0.049 (1.015)	0.026 (−0.555)
RD	−1.573 * (−1.991)	−0.516 (−0.703)	−0.674 (−0.800)	−1.728 ** (−2.139)
SIP	−0.011 (−0.404)	−0.015 (−0.597)	−0.026 (−0.892)	−0.015 (−0.523)
PCGDP	1.04×10^5 (0.813)	-5.63×10^6 (−0.480)	6.06×10^6 (0.449)	3.20×10^5 ** (−2.410)
PD	4.14×10^5 (0.089)	0.0002 (0.409)	0.0003 (0.646)	0.0002 (−0.481)
PRE	−0.217 (−1.315)	−0.247 ** (−2.123)	−1.508 *** (−4.530)	−0.392 (−1.062)
TEM	0.543 *** (7.021)	0.484 *** (6.327)	0.621 *** (6.415)	0.282 *** (−4.705)
R ²	0.843	0.892	0.879	0.918
Log likelihood	−1043.98	−1019.82	−1071.09	−1067.61
AIC	2111.96	2063.64	2166.19	2159.22
p-value	0.000	0.000	0.000	0.000

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

Table 4 shows the results of the regression model, in which the R², log-likelihood, AIC, and other statistical results are significantly higher, indicating that the SLM regression model in this study has a relatively good fit. This model can accurately assess the impact of seasonal changes in the urban form on PM_{2.5} concentrations. In addition, the seasonal analysis according to the GWR model shows that the regression coefficients of the impact of each city's form index on the level of PM_{2.5} pollution have different spatial distribution patterns (Figure 7). As shown in Table 4, seasonal variation significantly affects the relationship between urban form and PM_{2.5} concentration.

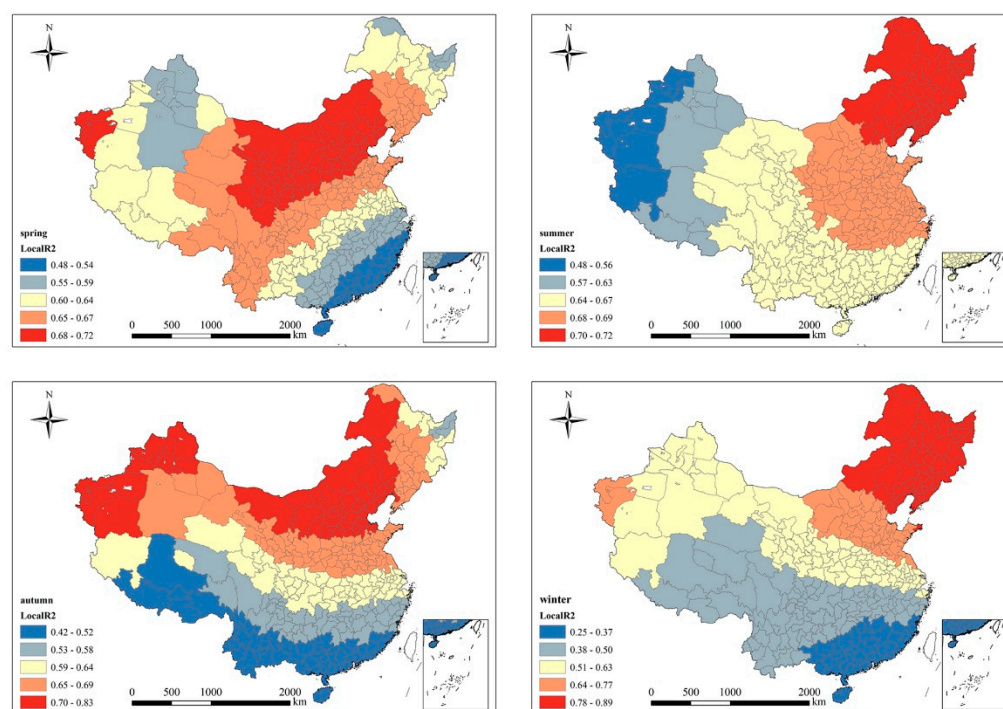


Figure 7. Local R² derived from multivariate GWR model in spring, summer, autumn, and winter.

The four main findings of this study are summarized in the following: firstly, a significant correlation exists between urban form and PM_{2.5} concentrations in all four seasons, with the highest R² value in winter. Secondly, the temperature and precipitation in the control variables always exerted a significant impact on PM_{2.5} concentrations, while other socioeconomic indicators had no significant impact on PM_{2.5} concentrations. Thirdly, the effect of PLAND and PM_{2.5} concentrations is significantly positively correlated, while that of LPI and PM_{2.5} concentrations is significantly negatively correlated in spring, summer, and winter. Fourthly, a negative correlation was found between the density of urban road network and PM_{2.5} concentrations. Specifically, in spring, LPI, PLAND, and RD significantly impact PM_{2.5} concentrations, with regression coefficients of -0.289 , 0.243 , and -1.537 , respectively. In the summer, urban compactness ($AI = 0.052$) can decrease the PM_{2.5} concentration to some extent. LPI (-0.489) and PLAND (0.320) were all significantly associated with PM_{2.5} concentrations. In the autumn, the correlation between urban form and PM_{2.5} concentrations was not significant. In the winter, PLAND (0.240) was significantly positively correlated with the PM_{2.5} concentrations. LPI (-0.258) and RD (-1.728) were significantly negatively correlated with PM_{2.5} concentrations.

Therefore, data analysis showed that seasonal change exerts a certain influence on the relationship between urban form indicators and PM_{2.5} concentrations. Especially in spring and winter, increasing the connectivity of urban construction land and improving the efficiency of land use within a city can effectively decrease urban PM_{2.5} concentrations [15]. Moreover, increasing the road connectivity also exerts a significant effect on reducing atmosphere pollution. However, the season of autumn does not exert a significant effect on the relationship between urban form and PM_{2.5} concentrations. In contrast, the indicators between urban form and PM_{2.5} are more significantly correlated in spring and winter, and relatively less in summer and autumn. Firstly, the previous analysis on an annual scale shows that the compact and continuous urban construction land, the reduction of urban land fragmentation, and the reasonable road network density are all conducive to reducing urban atmospheric pollutant emissions. Secondly, seasonal changes are mainly reflected by different climatic variables. The strong Asian monsoon during summer and the subtropical high during autumn result in favorable weather conditions that clean the air from atmospheric pollutants, as they enhance the mobility of the atmosphere above

urban centers. The summer monsoon climate moves more precipitation to North China, and at the same time increases the wind speed under the subtropical high pressure. These meteorological conditions are conducive to reducing atmosphere pollutants [16]. Under such climatic conditions, small changes in the structure of building areas or land areas near the ground exert little impact on atmospheric pollutants. Finally, low temperatures in winter and spring cause the atmospheric flow to sink and wind speeds are also lower than in summer [15]. In addition, more coal is burnt in the north in winter, and the resulting atmospheric pollutants cannot easily spread and remain concentrated near the ground. Under these conditions, the irregular urban form near the ground has a more significant impact on PM_{2.5} concentrations. Therefore, seasonal changes exert a significant impact on PM_{2.5} concentrations. When exploring the relationship between urban form and PM_{2.5} concentrations, focusing on the results of spring and winter is more effective.

There are many factors that affect the PM_{2.5} concentration, but our research just focused on the urban form. In addition, industrial areas, greenness area, vegetation coverage, transportation and other factors also have a significant impact on PM_{2.5} concentration. Therefore, there are some limitations of this study. Firstly, more influencing factors should be considered, such as the emission forces, change of pollution effects, LHI [20], meteorological conditions, the development levels of different cities and environmental conditions that surround the region of interest. These factors have an important effect on PM_{2.5} and are also associated with PM_{2.5} through interaction. They can all improve our indicator system. By selecting typical cities for further research, further problems may be identified. Secondly, the classification accuracy of urban land use data can be improved, and the impact of different land use patterns of urban construction land on PM_{2.5} pollution can be explored. For example, extract the industrial area in city for research. Thirdly, experiment with different research methods and data sources. For example, compare the remote sensing estimated PM_{2.5} concentration obtained by different sensors; compare the results of different research models; compare the impact levels of more influencing factors on the PM_{2.5} concentration, and so on.

5. Conclusions

Exploring the relationship between PM_{2.5} pollution and urban form helps to better understand the distribution of PM_{2.5} pollution, provide suggestions for urban planning, and the government with exploring a more sustainable and environmentally friendly development model for cities. Therefore, this study selected 340 prefecture-level cities in China to explore the relationship between urban form and PM_{2.5} pollution via regression analysis and GWR model. The following lists the main conclusions and recommendations:

Firstly, the distribution of PM_{2.5} pollution showed spatial heterogeneity, with an increasing trend from northwest to southeast. Areas with high PM_{2.5} concentrations are mainly located on the North China Plain, which is greatly affected by human activities. The southwest and parts of the northwest are affected by climatic factors, and thus, their PM_{2.5} concentrations are also high. The climatic and human activity conditions on the Qinghai–Tibet Plateau are not conducive to the accumulation of PM_{2.5} pollution, and thus, this area was always less polluted. Affected by seasonal changes, the PM_{2.5} concentration decreases in the respective order of winter, spring, autumn, and summer.

Secondly, most urban form indicators are significantly related to PM_{2.5} concentration. The results of the GWR model show that the spatial distribution decreases from north to south, and the urban form indicators system exerts a stronger influence on cities in northern regions. In general, better continuity is associated with a lower the degree of fragmentation, and a higher compactness and reasonable density of the road network are conducive to reducing the PM_{2.5} concentrations. In addition, meteorological conditions are also conducive to the diffusion and reduction of atmospheric pollutants. Thirdly, on a seasonal scale, seasonal changes impact pollution levels, but not all urban form indicators are significantly related to PM_{2.5} concentrations. Affected by seasonal changes, more urban

form indicators were significantly correlated with PM_{2.5} concentrations during spring and winter compared with summer and autumn.

This research used a large data set and confirmed that a good urban form exerts a positive effect on reducing PM_{2.5} concentrations. In the future development, the proportion of the secondary industry in the urban area should be reduced, green industries should be developed, atmospheric pollutant treatment technologies should be improved, and pollution sources should be controlled to reduce emissions. In areas with low pollution values, protection measures should be increased. More importantly, in urban planning, the blind expansion of urban land should be avoided, the compactness of the urban form, the efficiency of land use, and the transportation network in the city should be improved, and various forms of public transportation should be offered.

There are three main limitations of this study. Firstly, many factors influence PM_{2.5} pollution, and the geographical location, climatic conditions, and development levels of different cities are all different. By selecting typical cities for further research, further problems may be identified. Secondly, the classification accuracy of urban land use data can be improved, and the impact of different land use patterns of urban construction land on PM_{2.5} pollution can be explored. Thirdly, different research methods and data can be used to improve the accuracy of pollution source data, as well as research models, and different data methods can be utilized to further explore the estimation of PM_{2.5} levels and relevant influencing factors.

Author Contributions: Conceptualization, Y.L. and L.H.; methodology, Y.L.; software, Y.L.; formal analysis validation, Y.L.; formal analysis, Y.L.; writing—original draft investigation, Y.L.; investigation, L.H.; data curation, Y.L.; visualization, W.Q.; writing—review & editing, A.L. and Y.Y.; supervision, Y.Y.; funding acquisition, Y.Y. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Strategic Priority Research Program of the Chinese Academy of Sciences (XDA20010201).

Data Availability Statement: MERRA-2 dataset is available at <https://daac.gsfc.nasa.gov/> (accessed on 10 August 2021).

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

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