

Temporal and spatial impacts of land transfer on PM2.5 concentration in 285 cities of China

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Abstract: The threat of fine particulate matter concentration (PM2.5) is increasing globally, Tackling this issue requires an accurate understanding of its trends and drivers. The article investigates the PM2.5 characteristics of 285 prefecture-level cities in China from 2000-2018 based on multiscale geographically weighted regression(MGWR), and the results show that (1) previous studies based on classical MGWR models may be somewhat unstable, while MGWR can reflect the scale of influence of different variables on the dependent variable, and its regression results are more reliable.

(2) PM2.5 is very sensitive to carbon emission(CE) factors, and there is a high degree of spatial heterogeneity, and the influence scale of location is the smallest among all variables, close to the municipal scale. (3) In 2000, the constant term all, IS, OFT, CE, and LT positively affect PM2.5, while GDP (jurisdiction) and UR negatively affect PM2.5; in 2010, the constant term all, GDP (jurisdiction), IS, OFT and LT positively affect PM2.5, while UR and CE negatively affect PM2.5; in 2018 the constant term all, IS, OFT and CE factors positively affect PM2.5, and GDP (jurisdiction), UR and LT negatively affect PM2.5.

Keywords: PM2.5; GDP; MGWR; land transfer; industrial structure

1. Introduction

In recent years, fine particulate matter with aerodynamic diameters ≤ 2.5 mm (PM2.5) has become a national crisis in most developing countries, especially in China[1,2]. Epidemiological studies have indicated that PM2.5 is one of the major causes of cancer, heart and respiratory diseases [2,3] Increasing air pollution has been accompanied by severe fine particulate pollution events in recent decades[2,4]. Approximately 0.7 million to 2.2 million people die each year in China from air pollution-related problems[5,6]. Epidemiological studies have shown that PM2.5 is one of the leading causes of cancer, heart disease, and respiratory diseases[7,8]. The United Nations General Assembly proposed the Sustainable Development Goals (SDG) as an important health indicator related to air pollution. In 2015, the value was very low in China[9]. During the urbanization process in recent decades, the national Land transfer have grown from 45,000 hm² in 1999 to 66.6 million hm² in 2018, and the rapid increase in Land transfer has also led to new characteristics of urban land space. Rapid economic growth driven mainly by high energy consumption and economic development characterized by low eco-efficiency, especially the real estate sector, as an industry that relies on Land transfer to enable rapid development, has driven China's high economic growth. In 2020, the value of commercial property transactions nationwide achieved year-on-year growth of 8.7%, and total sales have exceeded ten trillion yuan, making China by far the world's largest real estate trading nation. Real estate, as a special comprehensive commodity, involves a wide range of industrial chains and is inextricably linked to other industries. The rapid development of the real estate industry has driven the growth of China's GDP, as well as the development of the construction, wholesale and retail industries, business services and financial industries, and the process of urbanization in China.

Cities are the basic spatial form in the process of urbanization, and the rapid development of cities depends on Land transfer[10], which is a typical basic way of transferring land-use rights in China, and the rapid rate of Land transfer in China in the last 20 years, most typically from 2005 to 2013, Due to a large number of transfers, has led to the rapid development of Chinese cities[11,12], in which problems caused by Land transfer are common, with social problems, including social, economic and environmental problems. The 285 prefecture-level cities counted across the country have highly uneven regional development, and as a result, these cities located in different geographical regions present different natural conditions, income levels, energy consumption, and environmental pollution problems[13,14]. And what is the intrinsic relationship between economic development driven by Land transfer and PM2.5 pollution, are there differences in the impact of PM2.5 pollution between different cities, and how can these differences be understood? The multivariate analysis involves the non-stationarity of spatial relationships, which cannot be addressed by ordinary constant-coefficient spatial econometric models.

Due to the vast size of China and the wide variation in economic, social, and environmental issues across regions, the reasons for the faster and stronger influence on Land transfer vary. Therefore, in addition to analyzing the influencing factors of Land transfer, it is also very necessary to reveal the spatial characteristics of local influencing factors and the extent of spatial heterogeneity among different cities. The results can be used to improve the current or existing PM2.5 pollution problems, rather than following similar approaches or policies of other cities to mitigate the problems caused by Land transfer.

Chul-Hee [15] explained the effect of three factors, urbanization rate, population and vegetation greening rate, on PM2.5 concentrations through Mann-Kendal trend and statistical analysis, but they used only representative drivers to identify the relationship between macro changes and PM2.5, especially using socio-environmental factors, which are potential causes rather than emission sources; Qiang [16] simulated the change in PM2.5 concentrations between 2013 and 2017 through a weather study and predictive model-community multi-scale air quality model, analyzing the main drivers of PM2.5 pollutants mainly at the industrial level, as there are too few publicly available observations of PM2.5 chemical composition to support a comprehensive trend assessment; Ximing Luo [17] analyzed the drivers of PM2.5 by three factors, population, economy and land, through FMOLS model, but did not consider the spatial spillover effects of urban PM2.5 pollutants, and the three independent variables selected may not fully reflect the urbanization process.

Compared with previous studies, this study focuses on the analysis of urban PM2.5 concentrations, analyzes the driving factors behind them from historical PM2.5 concentrations[18,19], and analyzes the influencing factors behind them from six factors: gross domestic product (jurisdiction), industrial structure, urbanization rate, openness to foreign trade, carbon emissions, and Land transfer based on a multiscale geographically weighted regression model, which can analyze the changes that occur at different geographical The model can analyze the changes occurring within different geographical scales and can distinguish the scale of influence of different variables on the dependent variable, and the results appear to be more robust compared with the traditional geographically weighted regression model. Based on this, the estimation of each set of parameters model is more accurate at each location, which can better reveal the influence of influencing factors on the spatial variation of PM2.5 concentration.

The remainder of this study is as follows: the second part is a spatial autocorrelation and pairwise scaled geographically weighted regression model. The third part reveals the general

characteristics and the spatial accumulation characteristics of global PM_{2.5} concentrations over the Chinese landscape. The fourth part systematically and objectively analyzes the empirical results of the correlation between PM_{2.5} concentrations and PM_{2.5} concentrations and analyzes the corresponding influencing factors from national and local perspectives. Part V presents the conclusion.

2. Methodology

2.1 Spatial autocorrelation

Spatial autocorrelation statistics [3,20] is a fundamental property used to measure geographic data and can be divided into global and local spatial autocorrelation analysis. The degree of interdependence between data at one location and data at other locations is often referred to as Spatial dependence [21,22]. The global Moran's I index measures the overall trend of spatial correlation of the values of the attributes of the spatially adjacent regional units across the study area and is calculated as follows:

$$\text{Moran's } I = \frac{\sum_{i=1}^n \sum_{j=1}^n W_{ij} (X_i - \bar{X})(X_j - \bar{X})}{S^2 \sum_{i=1}^n \sum_{j=1}^n W_{ij}}, \quad S^2 = \frac{1}{n} \sum_{i=1}^n (X_i - \bar{X})^2 \quad (1)$$

where $i \neq j$ and n is the number of spatial units involved in the analysis. x_i and x_j denote the observed values of factor X in spatial cells i and j , respectively. W_{ij} is the spatial weight matrix, which indicates the proximity or distance relationship between regions i and j . Significance can be detected based on the test statistic, with a general significance level of $\alpha = 0.05$.

The global Moran index value [10,23] range is $(-1, 1)$, and a positive (negative) Moran index value at a given significant level indicates the overall spatial clustering (divergence) of the observed objects in the global domain. The local clustering characteristics of the observed objects can be further portrayed by the LISA plot, which can be divided into four quadrants, with H indicating variable values above the mean and L indicating variable values below the mean. The first quadrant (HH) indicates that the high-value region is surrounded by high-value neighbors; the second quadrant (HL) indicates that the high-value region is surrounded by low-value neighbors. The third quadrant (LL) indicates that low-value regions are surrounded by low-value neighborhoods; the fourth quadrant (LH) indicates that low-value regions are surrounded by high-value neighborhoods; HH and LL indicate that regions are less different from their neighbors, regions with higher or lower values are concentrated, while LH and HL indicate that regions are somewhat different from their neighbors in terms of variable values.

2.2 Multi-scale geographically weighted regression models

The Multiscale Geographically Weighted Regression (MGWR) [24] model was developed to improve on the geographically weighted regression model by re-modeling the traditional geographically weighted regression model GWR [25] as a Generalized Additive Model (GAM) [26] and extending this framework to MGWR to derive local parameter estimates of standard errors, which can derive separate bandwidth and smoothing coefficients for each covariate, the model is critical for model fitting between traditional global models and for adjusting for multiple hypothesis tests. The computational equation is as follows.

$$y_i = \sum_{j=1}^k \beta_{bwj}(u_i, v_i) x_{ij} + \varepsilon_i \quad (2)$$

where: bwj represents the bandwidth used for the regression coefficient of the j th variable. each

regression coefficient of MGWR β_{bwj} is obtained based on local regression and the bandwidth has specificity, and this is the biggest difference from the classical geographically weighted regression model (GWR), in which β_{bwj} the bandwidths of all variables are the same. The kernel functions and bandwidth selection criteria for the multi-scale geographically weighted regression model (MGWR) continue to use several classical kernel functions and bandwidth selection criteria from the classical geographically weighted regression model (GWR). In this article, we use the most commonly used quadratic kernel function and AICc criterion.

The classical geographically weighted regression model (GWR) uses least squares estimation, while the multi-scale geographically weighted regression model (MGWR) uses the generalized additive model (GAM). The formula is as follows.

$$y = \sum_{j=1}^k f_j + \varepsilon(f_j = \beta_{bwj}x_j) \quad (3)$$

For multi-scale geo-weighted regression model (MGWR) initial estimates, we choose the classical geo-weighted regression model (GWR) as the initial estimate and determine the initialized residual by calculating the difference between the true value and the initial estimate, which is $\hat{\varepsilon}$.

$$\hat{\varepsilon} = y - \sum_{j=1}^k \hat{f}_j \quad (4)$$

Residuals $\hat{\varepsilon}$ plus the first additive term \hat{f}_1 with the first independent variable x_1 . Perform a classical geographically weighted regression model (GWR) regression to find the optimal bandwidth bw_1 and a new column of parameter estimates \hat{f}_1 and $\hat{\varepsilon}$ to replace the previous estimates. Next the residuals plus the second additive term \hat{f}_2 with the second variable x_2 using the same regression algorithm and updating the parameter estimates for the second variable \hat{f}_2 and $\hat{\varepsilon}$. And so on until the last independent variable x_k (kth independent variable). The above algorithm as a whole is one step, and the computation is repeated until the estimation convergence computation converges. This study uses the classical residual sum of squares (RSS) change ratio as the convergence criterion.

$$SOC_{RSS} = \left| \frac{RSS_{new} - RSS_{old}}{RSS_{new}} \right| \quad (5)$$

where. RSS_{old} represents the sum of squared residuals from the previous step. RSS_{new} represents the sum of squared residuals from this step.

2.3 Variable selection and data sources

In this study, PM2.5 concentration was defined as the dependent variable. According to the above research, rural labor force, planting crop selection and energy industry all have a certain impact on PM2.5 concentration. Reviewing the previous studies, we also found for example industrial structure, energy structure, etc. as possible influencing factors[27–29]. However, the lack of some city-level data and the possibility of multicollinearity problems, some of these variables may lead to inaccurate regressions. Therefore we first try to select appropriate indicators as explanatory variables.

Land transfer (Lt)

In China, the transfer of land use right is the act that the state, as the land owner, transfers the state-owned land use right of a certain plot to the land user within a certain period of time[30–32], and the land user pays the land use fee to the state. Land transfer is the basis for urbanization and a prerequisite for China's rapid economic development. The rapid pace of Land transfer in China in the last 20 years[33–35], The most typical is from 2005 to 2013, has led to the rapid development of China's cities and towns and driven the country's rapid economic development[36,37]. Among them, the problems caused by land transfer are common, especially social problems, economic problems and environmental problems. This paper selects it as the explanatory variable to explore whether

land transfer can indirectly affect the change of PM2.5 concentration.

Urbanization rate (Ur)

Urbanization rate is a measurement index of urbanization, which generally adopts demographic index, that is, the proportion of urban population to the total population (including agriculture and non-agriculture). According to the estimation of the United Nations, the urbanization rate of developed countries in the world will reach 86% in 2050, and that of China will reach 71.2% in 2050[17,38]. In this paper, it is chosen as an explanatory variable to explore whether different changes in population can promote the development of cities, indirectly promote the transformation of land properties and strengthen land transfer.

Industrial structure (Is)

Industrial structure indicators mainly represent the ratio of the secondary industry's GDP to the region's GDP[39,39,40]. China is a developing country, mainly relying on the secondary industry, with the largest proportion of the population engaged in the secondary industry[41,42], which can promote China's economic development and urbanization[43,44]. Choosing industrial structure indicators to explain PM2.5 concentration is a direct and effective way.

Carbon emissions (Carbon emissions; Ce for short)

Carbon emissions are the average greenhouse gas emissions generated during the production, transportation, use, and recycling of that product[45–47]. After entering the 21st century, China's carbon emissions have grown rapidly and its share in the world has been on an increasing trend[48,49]. the world share of China's total carbon emissions was 18% in 2005 and exceeded 25% in 2016. global Carbon Atlas statistics show that the share of China's carbon emissions reached 27.2% in 2017[29,50]. The trend of carbon emissions in China has some similarities with the change of PM2.5 concentration, and this study chooses carbon emissions as the explanatory variable to explore whether there is some causal relationship between carbon emissions and PM2.5 concentration.

The openness of foreign trade (Openness of foreign trade; OFT for short)

The openness of foreign trade is the starting point for China's rapid economic development[51–53], but it has also caused the development of mixed economic policy mechanisms and transmission mechanisms, which has brought certain risks to China's economy[54,55]. The increase of openness to foreign trade has brought many employment opportunities to the development of China's coastal cities[56,57], promoting the rapid rise of the local economy and driving the influx of inland workers to the coastal development, while also further increasing the area of Land transfer by the government, which has a strong correlation between openness to foreign trade and Land transfer in the analysis; openness to foreign trade is the ratio of foreign direct investment to the regional gross output value, which to a certain extent The openness of foreign trade is the ratio of foreign direct investment to regional GDP, which to a certain extent can reflect the degree of China's external linkage and openness.

From 2001 to 2018, we collected cross-sectional data from 285 cities in China, limited by space, this paper focuses on the years 2000, 2010, and 2018. 2000 is the initial year of the western development, the center of economic activity has shifted from the southeast coast to the central and western regions, so it is important to reveal the economic activity and PM2.5 concentration[58]. 2010 is the year of China's real estate market heyday, China's land sales are fast and intense, and China's infrastructure speed is also amazing, so it also has some research value. The year 2010 is the heyday of China's real estate market, China's Land transfer are fast and intense, and the speed of China's infrastructure is equally impressive, so it also has some research value[59–61]. 2018 is the year when

China's secondary industry-based economic construction stabilizes[62,62,63], and it is important to reveal the driving factors of PM2.5 concentration. The source of land grant data is with China Land Market Network (<http://www.landchina.com>), and the land grant data of this website in the past years are crawled through python program editor. The data of China's urban population, total population data, total regional output value, total output value of the secondary industry, and total foreign investment were obtained from China Urban Statistical Yearbook and China Economic Statistical Yearbook.

Table 1: Description of variables

Variable Name	English abbreviation	unit	Variable Description
constant term (math.)	Intercept	μg/m3	The intercept term of the model, reflecting the effect of zone
gross domestic product (GDP)	GDP	ten thousand dollars	Annual gross domestic product of prefecture-level municipalities
industrial structure	Is	%	The ratio of gross domestic product to GDP in the secondary sector
urbanization rate	Ur	%	The non-agricultural population as a percentage of the total population
Openness to foreign trade	OFT	%	Foreign direct investment to GDP ratio
carbon emission	Ce	mt	Total annual carbon emissions from prefecture-level municipal jurisdictions
Land transfer	Lt	hectares	Total land sales in prefecture-level municipalities

3. Results and discussion

3.1 Description of the spatial distribution of PM2.5 concentrations

PM2.5 concentrations from 285 Chinese cities are shown in Figure 1, where the average PM2.5 concentration was 33.348 micrograms per cubic meter in 2000, 39.874 micrograms per cubic meter in 2010, and 26.249 micrograms per cubic meter in 2018, from the Chinese version of the map, can It can be seen that the areas with relatively high PM2.5 concentration are mainly concentrated in the Yangtze River Delta city cluster, Yangtze River midstream city cluster, Pearl River Delta city cluster, Beijing-Tianjin-Hebei city cluster, and Chengdu-Chongqing city cluster, these areas are mainly represented by the capital cities of the provinces with relatively strong economic capacity, compared with the prefecture-level cities, the capital cities of the provinces usually drive the development of the prefecture-level cities and radiate the whole provincial area. The spatial distribution of PM2.5 concentrations shows that the central region is slightly higher than the eastern region, and the central region is higher than the western region (see Figure A.1 for the regional division). The highest PM2.5 concentration value in China at the beginning of 2000 was in Chengdu (152.146 μg/m3), and the lowest PM2.5 concentration was in Lhasa (5.246 μg/m3). 2000, with the western development plan, the economic centers were mainly concentrated in the central and western regions, and the cities with higher PM2.5 concentration in 2000 were mainly concentrated in the central and western regions. After 2000, the PM2.5 concentration in Chinese cities increased every year, which also reflects the fact that the Chinese real estate market also started to rise from this time, and the urbanization process in China has only started to kick off since then. In 2010, the national average PM2.5 concentration increased significantly compared to the year 2000. The highest Sichuan Zigong

PM_{2.5} concentration was 101.190 micrograms per cubic meter, and only one city exceeded 100 micrograms per cubic meter in 2010, a significant decrease in the high point compared to 11 in 2000. The intensity of PM_{2.5} concentrations across the country in 2018 fell back compared to 2010, and the highest PM_{2.5} concentration in 2018 was in Henan Province's Luohe City at 61.189 micrograms per cubic meter, the high point has fallen back significantly compared to previous years, the lowest point with data is Lhasa City at 3.484 micrograms per cubic meter, the concentration high and low points are relatively flat, in the 2018 year we have been difficult to see the obvious difference between the middle and west from the PM_{2.5} concentration average graph, it has broken the boundary line, proving that China's urbanization development is in full swing, China's various There is a certain linkage and strong radiation between the development of large cities in China.

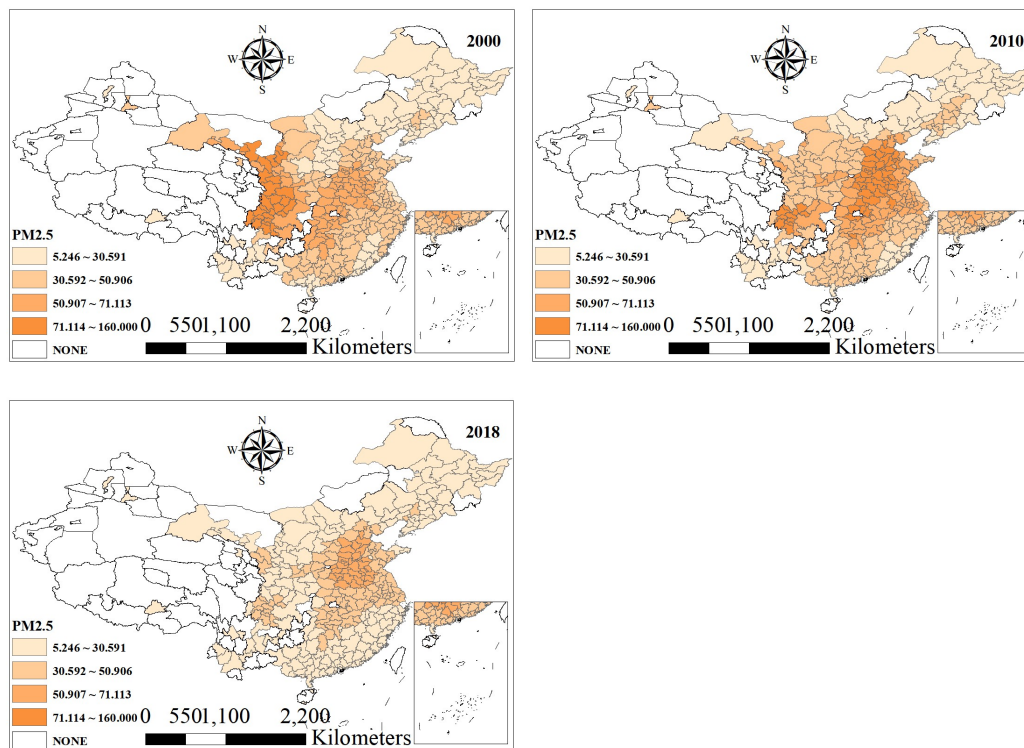


Figure 1. Distribution of PM_{2.5} concentration in China

3.2 Spatial accumulation characteristics of PM_{2.5} concentrations

The values of global Moran's I obtained by analyzing the global spatial autocorrelation of PM_{2.5} concentration in China are shown in Figure 2, which are 0.686, 0.758, and 0.766 in 2000, 2010, and 2013, respectively, which satisfy the 1% ($p < 0.01$) level and prove to pass the 99% significance level test, while Moran's I index as a whole shows a certain degree of fluctuating upward trend, indicating that there is an obvious positive correlation in the spatial distribution of PM_{2.5} concentrations with significant clustering characteristics, and the spatial autocorrelation of PM_{2.5} concentrations on the time scale has a tendency to further strengthen.

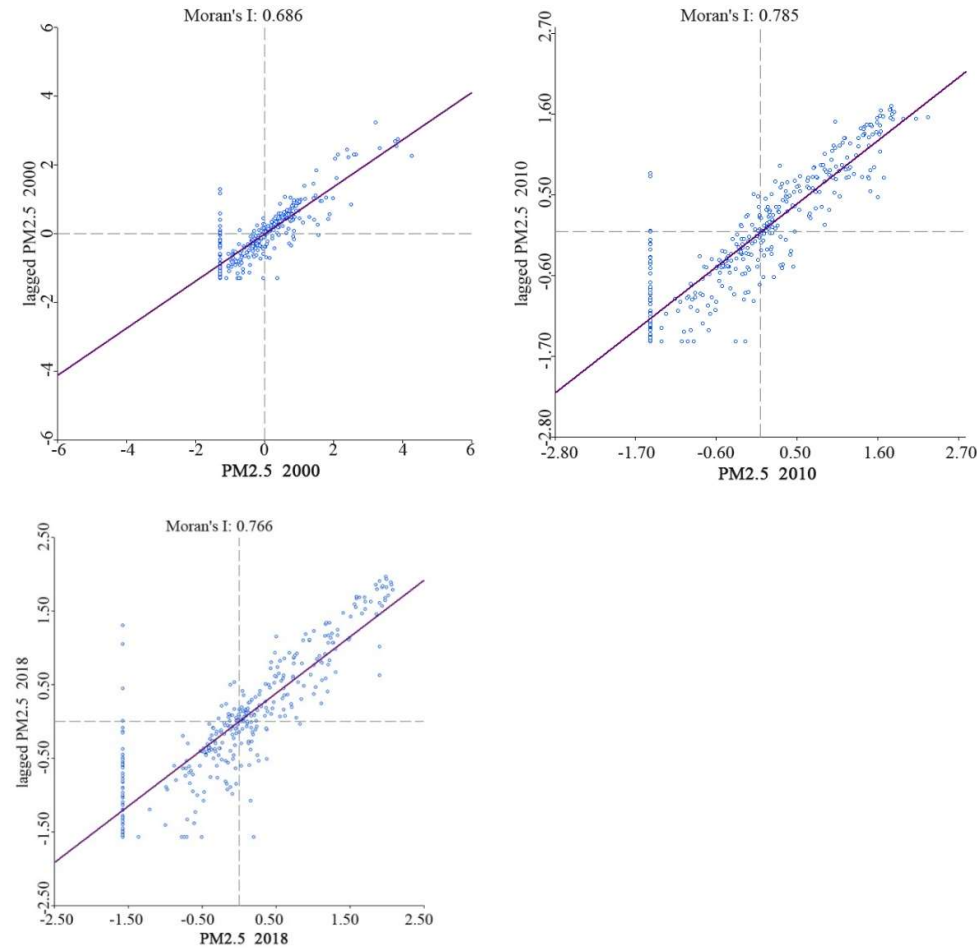


Figure 2. scatterplot of PM2.5 concentration changes in China in 2000, 2010 and 2018

In addition, local Moran is calculated by revealing four local spatial linkage patterns, as shown in Figure 3, around 2000, due to China's western development plan, driven by Sichuan, Shaanxi, Gansu, etc., as well as the central and western regions of Henan, etc. exhibit obvious high-high clustering patterns; in 2010, the Beijing-Tianjin-Hebei city cluster and the surrounding Henan-Jiangsu-Zhejiang region; in 2018, the Beijing-Tianjin-Hebei city cluster and the middle and lower reaches of the Yangtze River urban agglomeration areas show a clear high-high clustering pattern. This is because these places rely on their superior geographical locations and can attract migrant workers, which leads to rapid local economic development and drives the development of the local real estate business, and many migrant workers sometimes settle locally, thus driving up PM2.5 concentrations. In northwest cities show a low-low clustering pattern, northwest economic development is backward, residents choose foreign workers; some relatively developed areas of Chongqing and around Guangdong Province show a clear high-low clustering pattern. The low-high clustering pattern is generally in the vicinity of the high-high clustering pattern because the economic development of these areas is relatively lagging compared to the high-high clustering cities. Interestingly, no obvious high-high agglomeration phenomenon is found in the Pearl River Delta urban agglomeration, which may have a significant relationship with the local economic development pattern. Most of the foreigners who come to work in such places are mostly from Hunan Province and Jiangxi Province and are generally engaged in traditional manufacturing industries, which belong

to the lower strata of the industry and do not have the certain economic strength to choose to settle in the area.

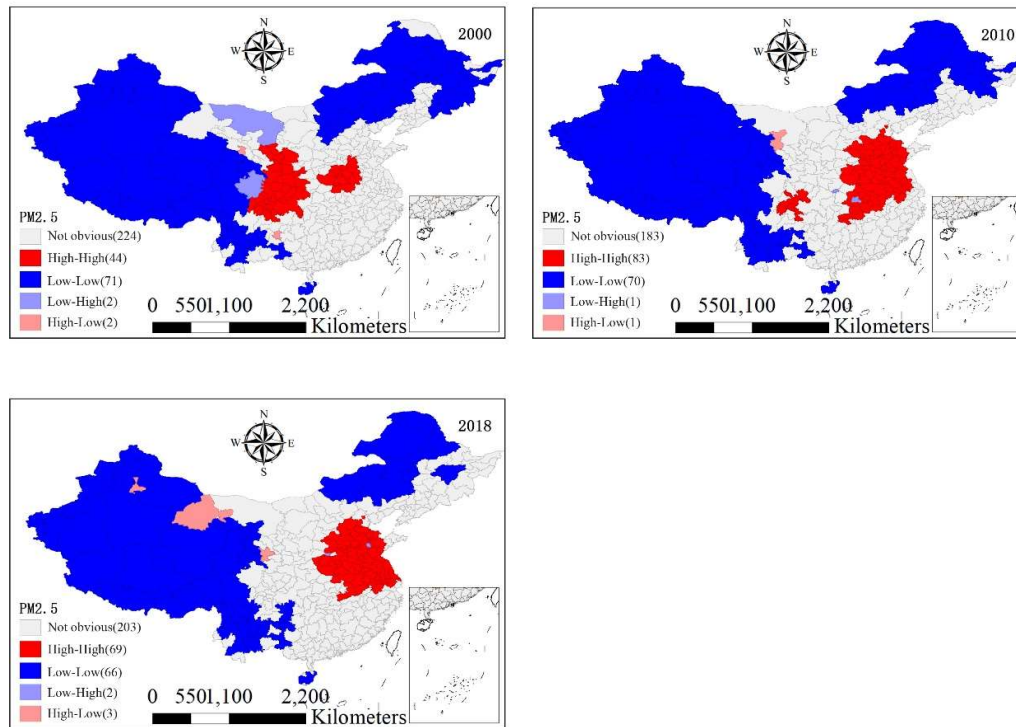


Figure 3. four local spatial association patterns in 2000, 2010 and 2018

3.3 Comparative analysis of models

As shown in Table 1, the goodness-of-fit R^2 of MGWR is higher than that of classical GWR and the AICc value is lower than that of classical GWR, thus it can be judged that the results of MGWR are better than those of classical GWR. In terms of the number of valid parameters, MGWR is smaller than GWR in 2000 and 2010 and larger than GWR in 2018, which indicates that the numerical size affects the results of the valid parameters in, and the residual sum of squares is smaller than GWR in both 2010 and 2018 MGWR, indicating that its use of reasonable effective parameters yields regression results that are closer to the true value. On the other hand, in terms of the overall regression coefficients, the individual coefficients of MGWR are significant overall and close to the most realistic results, as shown in Figure 4, while none of the classical GWR coefficients are significant overall. It is very unreasonable that none of these variables are significant in the PM2.5 concentration change, and this also indicates that the classical GWR, by ignoring the diversity of the action scales of the individual variables, causes a large amount of noise and bias, which in turn leads to the non-robustness of the regression coefficients. Therefore, this study uses a multi-scale geographically weighted regression model analysis can make the conclusions closer to the real reality.

Table 2: Indicators of classical and multiscale geographically weighted regression models

Type of indicator	MGWR			Classic GWR		
	2000	2010	2018	2000	2010	2018
The goodness of fit R^2	0.180	0.145	0.151	0.179	0.140	0.151
Number of valid parameters v_1	51.758	71.317	60.493	59.786	187.632	58.319
AICc	432.524	783.391	781.379	468.452	2548.181	2244.475
residual sum of squares	234.555	244.566	242.851	81.312	117017.374	40464.012

3.4 Scale analysis

As can be seen from Table 2, MGWR can directly reflect the differential scale of action of different variables, while classical GWR can only reflect the average of the scale of action of each variable, and the bandwidth of classical GWR is 54 in 2000, 54 in 2010, and 54 in 2018. while by calculating MGWR, it is found that the scale of action of different variables varies greatly. In Table 3 of the MGWR regression results, the regression coefficients of three variables, GDP, urbanization rate, carbon emissions, and Land transfer, are significant overall. While the regression coefficients of the 2 variables, constant term, and openness to foreign trade, are not significant. The constant term indicates the effect of different locations on PM2.5 concentration when other independent variables are determined. Among them, this paper controls the factor of government intervention, so the constant term reflects the influence of other factors such as economic and social on PM2.5 concentration.

The bandwidths of GDP (jurisdiction) indicators are 122 km, 86 km, and 243 km, which are close to the scale of municipal administrative areas, and GDP is used at this level, which satisfies the scale relationship, so while assessing the impact of GDP on PM2.5 concentrations, it should have a city-wide effect mechanism, which is different for different municipalities. So the proposed GDP (jurisdictional) improvements should also be different, and not every municipality should have the same reform mechanism for GDP (jurisdictional). The bandwidth of urbanization rate is 86km, 45km, and 43Km respectively, this scale belongs to the city zoning level under the municipal scale, in the process of urbanization development, the impact on PM2.5 concentration, we need to explore the impact of the functional relationship of each region on PM2.5 concentration, to ensure that the function of each region has some connection, but each has its characteristics so that it is beneficial to the development of the city, and also to The reform of urbanization mechanisms varies from region to region.

Table 3. bandwidth between classical and multiscale geographically weighted regression models

Type of indicator	MGWR			Classic GWR		
	2000	2010	2018	2000	2010	2018
constant term (math.)	43	43	43	54	54	54
Gross domestic product(jurisdictions)	122	86	100	54	54	54
industrial structure	285	56	74	54	54	54
urbanization rate	86	45	43	54	54	54
Openness to foreign trade	43	43	284	54	54	54

carbon emission	78	45	43	54	54	54
Land transfer	285	100	143	54	54	54

Table 4. global regression p-value results

variable	2000	2010	2018
constant term (math.)	1.000	1.000	1.000
Gross Domestic Product (Bailiwick)	0.068	0.02	0.242
industrial structure	0.022	0.000	0.102
urbanization rate	0.000	0.000	0.114
Openness to foreign trade	0.666	0.926	0.000
carbon emission	0.012	0.627	0.001
Land transfer	0.060	0.430	0.625

3.5 Analysis of the spatial pattern of coefficients

3.5.1 Analysis results in 2000

The statistical description of the MGWR coefficients is shown in Table 4. The effect of location on PM2.5 concentrations, as reflected in the constant term, is positive and shows a clear structural phenomenon such as accumulation around a circle. The constant term takes values between -1.194 and 1.422 with a mean value of 0.129, which indicates that the national PM2.5 concentrations range from 5.249 to 1.442 $\mu\text{g}/\text{m}^3$ and that different regions have a significant effect on PM2.5 concentrations.

As shown in Figure 4a. The location reflected by carbon emissions has a positive impact on PM2.5 concentration, the northeast region, and the southwest region belong to the high-value area, the region is influenced by location factors, between 0.066 to 0.746 micrograms per cubic meter, the central region is relatively less influenced by location the annual PM2.5 concentration is between in -0.019 to 0.065 micrograms per cubic meter. 2008 when the whole country was In 2008, the whole country was still in the era of great development, and the northeast had been dominated by heavy industry and relatively more developed economy, so the urbanization process was relatively rapid and the PM2.5 concentration was higher, and the Chengdu-Chongqing urban agglomeration was located in the southwest, taking advantage of its natural geography and developing more rapidly, thus also determining the higher PM2.5 concentration at some level. The central region as a whole is developing more slowly, without natural geographical advantages and special industries as a driving force. The southeastern coastal area belongs to China's earlier economic development, the overall smooth, PM2.5 concentration has always been stable at a level that is not high or low.

As shown in Figure 4b, the effect of GDP on PM2.5 concentrations is negative, reflecting the higher PM2.5 concentrations in areas with higher GDP due to the higher GDP, taking values between -0.386 and 0.226, with a mean value of -0.046, indicating that for every 100 million Yuan increase in GDP, PM2.5 concentrations decrease by 0.046 micrograms per cubic meter. The regression map shows a decreasing influence of GDP on PM2.5 from west to east, in this order (except where data are not available). This is also consistent with the crude incremental era characterized by a more one-sided pursuit of GDP at this time. The western region has been heavily supported by national policies to develop the great northwest, which is richer in natural resources, so economic development is faster and the relationship between development and the environment is less handled.

Land transfer have a more positive impact on PM2.5 concentrations, as shown in Figure 4c, with values ranging from 0.048 to 0.089 and a mean value of 0.054, indicating that for every 1 hectare of

Land transfer, PM_{2.5} concentrations increase by 0.054 micrograms per cubic meter. The national map shows a strong stratification from north to south. The rapid economic development in the north relies overwhelmingly on the secondary industry of mineral resources, with a high demand for land, and Land transfer drive the rapid economic development of the construction industry, which also causes an increase in PM_{2.5} concentration at some level. The way of economic construction in the south is also different from that in the north, where the basic economic construction is dominated by handicraft and manufacturing industries, and the speed of Land transfer is lower than that in the north, and the change in PM_{2.5} concentration is less obvious. Therefore, we reasonably control the rate of Land transfer so that we can achieve a certain level of reduction in PM_{2.5} concentration.

The industrial structure factor significantly and positively influences PM_{2.5} concentration, reflecting that the greater the proportion of secondary industry in the industrial structure, which drives economic development, the more obvious the influence on PM_{2.5} concentration. As shown in Figure 4d, the industrial structure forms a band distribution from west to east, and the influence of secondary industry on PM_{2.5} concentration decreases in this order. The industrial structure takes values from 0.481 to 0.525, with a standard deviation of 0.005. This indicates that for every 1% increase in industrial structure, the PM_{2.5} concentration increases by 0.005 μg per cubic meter, and the impact of industrial structure on PM_{2.5} concentration is small.

The urbanization rate factor significantly and negatively affects PM_{2.5} concentrations as shown in Figure 4e. This indicates that for every 1% increase in urbanization rate, the PM_{2.5} concentration decreases by 0.017 $\mu\text{g}/\text{m}^3$, reflecting the fact that the urbanization rate does not have a significant difference on PM_{2.5} concentration in different areas, and the degree of influence is mainly concentrated in urbanized areas such as the eastern coast. The impact of urbanization rate on PM_{2.5} concentrations does not vary greatly across regions, and the degree of impact is mainly concentrated in the eastern coast and other areas with higher urbanization.

3.5.2 Analysis results in 2010

As shown in Figure 4f, the effect of GDP on PM_{2.5} concentrations is positive, reflecting that PM_{2.5} concentrations are higher in areas with higher GDP due to the higher GDP, taking values between -0.127 and 0.91, with a mean of 0.164 and a standard deviation of 0.256, indicating that for every 100 million yuan increase in GDP, PM_{2.5} concentrations decrease by 0.164 micrograms per cubic meter. The regression map, which is more like the 2000 regression map, shows that the influence of GDP on PM_{2.5} decreases from west to east, in this order (except where data are not available). Development plans in the Midwest are still guiding the high rate of economic development in China, and the incremental era of GDP is still being pursued at this time. The high rate of economic development has led to an increase in PM_{2.5} concentrations.

The impact of industrial structure is mainly concentrated in the southwest of Sichuan Province and the Beijing-Tianjin-Hebei urban agglomeration, compared with 2000, the industrial structure impact area is shifted to the east, the industrial structure takes the value of -0.127~0.488, the average value is 0.121, the standard value is 0.126. This indicates that for every 1% increase in industrial structure, the PM_{2.5} concentration increases by 0.121 micrograms per cubic meter. In terms of the absolute value of the coefficient, the degree of influence is in the middle of all variables.

The urbanization rate factor significantly and negatively affects PM_{2.5} concentration, as shown in Figure 4h. The urbanization rate in the northeast and the middle and lower reaches of the Yangtze River urban agglomerations has a high impact on PM_{2.5}, with values ranging from -1.024 to 0.235,

with a mean value of -0.17 and a standard value of 0.298. This indicates that for every 1% increase in the urbanization rate, the PM2.5 concentration decreases by 0.17 $\mu\text{g}/\text{m}^3$.

3.5.3 Analysis results in 2018

The significant and positive effect of the carbon emission factor reflects the significant change of PM2.5 concentration due to carbon emission, as shown in Figure 4i. The effect of carbon emissions on PM2.5 concentration is significant and accumulative in the energy-led economy of Northeast China, the more industrialized Beijing-Tianjin-Hebei city cluster, and Fujian. The values range from -0.237 to 0.625, with a mean value of 0.206 and a standard value of 0.182. This indicates that for every 10,000 tons of carbon emissions, the PM2.5 concentration increases by 0.206 $\mu\text{g}/\text{m}^3$, and the intensity of the effect is greater among all variables.

The factor of openness to foreign trade is significant and positive, as shown in Figure 4j. The effect of openness to foreign trade on PM2.5 concentration is mainly in the region dominated by the northeast and decreases from north to south. The mean value is 0.042 and the standard value is 0.004, indicating that for every 1% increase in openness to foreign trade, the PM2.5 concentration increases by 0.042 $\mu\text{g}/\text{m}^3$. This reflects the small effect of openness to foreign trade on PM2.5 concentrations.

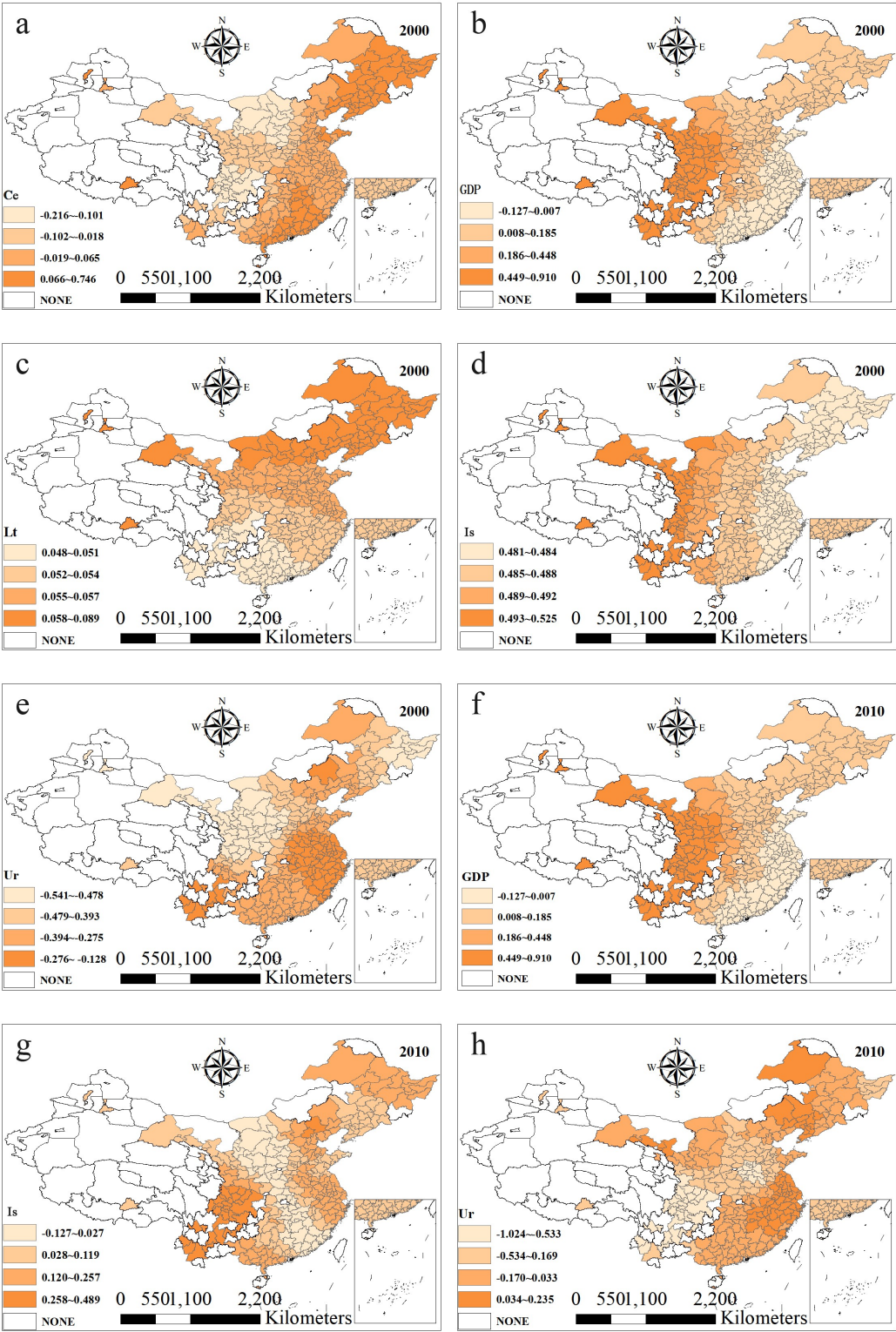
The industrial structure factor significantly and positively affects PM2.5 concentration, as shown in Figure 4k, the influence of industrial structure on PM2.5 is scattered, mainly concentrated in the northeast region, parts of Shanxi and Inner Mongolia, Xi'an region of Sichuan, and the middle and lower reaches of Yangtze River, and there is a clustering phenomenon. The values are taken from -0.231 to 0.138, with a mean value of 0.022 and a standard value of 0.086, which indicates that for every 1% increase in the share of secondary industry in the industrial structure, the PM2.5 concentration increases by 0.022 μg per cubic meter. In terms of the absolute value of the coefficient, the impact is of medium magnitude.

Table 5a. The statistical description of multi-scale geographically weighted regression coefficients

variable	average value			standard value		
	2000	2010	2018	2000	2010	2018
constant term (math.)	0.129	0.149	0.148	0.598	0.625	0.63
Gross Domestic Product (Bailiwick)	-0.046	0.164	-0.007	0.146	0.256	0.19
industrial structure	0.487	0.121	0.022	0.005	0.126	0.086
urbanization rate	-0.357	-0.17	-0.029	0.113	0.298	0.785
Openness to foreign trade	0.053	0.034	0.042	0.165	0.115	0.004
carbon emission	0.008	-0.063	0.206	0.093	0.332	0.182
Land transfer	0.054	0.133	-0.053	0.004	0.231	0.055

Table 5b. The statistical description of multi-scale geographically weighted regression coefficients

variable	minimum value			median			maximum number		
	2000	2010	2018	2000	2010	2018	2000	2010	2018
constant term (math.)	-1.194	-1.073	-0.896	0.163	0.137	-0.035	1.422	1.305	1.599
Gross Domestic Product (Bailiwick)	-0.386	-0.127	-0.209	0.01	0.067	-0.076	0.226	0.91	0.426
industrial structure	0.481	-0.127	-0.231	0.485	0.109	0.049	0.525	0.488	0.138
urbanization rate	-0.541	-1.024	-2.506	-0.364	-0.061	0.012	-0.128	0.235	2.524
Openness to foreign trade	-0.334	-0.151	0.037	0.021	0.016	0.042	0.471	0.526	0.066
carbon emission	-0.216	-0.827	-0.237	0.026	0.072	0.253	0.746	0.385	0.625
Land transfer	0.048	-0.128	-0.16	0.054	0.042	-0.066	0.089	0.653	0.075



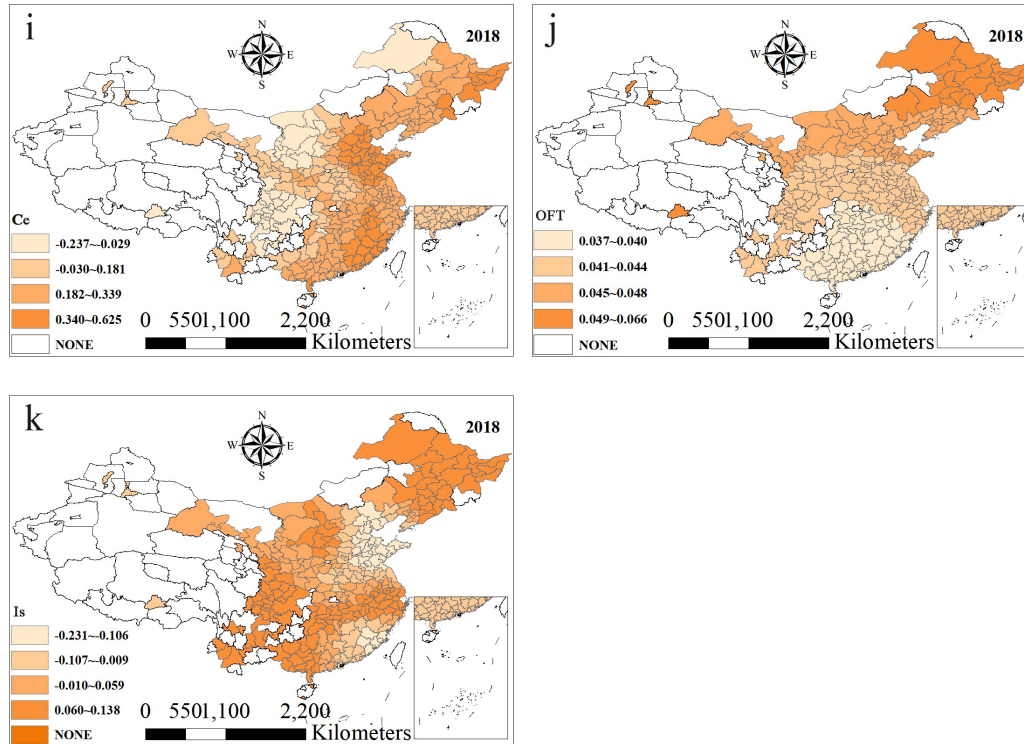


Figure 4. spatial pattern of multi-scale geo-weighted regression coefficients

5. Conclusions and recommendations

5.1 Conclusions

This paper, MGWR with statistical inference, which is at the forefront of academia, is applied to the empirical study. Combining national PM_{2.5} concentrations and other relevant data, for the spatial differentiation and spatial scale differences of national PM_{2.5} concentrations from 2000-2018, the following conclusions are obtained.

1: The results of MGWR are more reliable compared to classical GWR. Previous studies based on classical GWR may have been somewhat unstable. This is mainly due to the ability of MGWR to capture different scales of influence of different variables thus avoiding capturing too much noise and bias.

2: Analyzed from a national and local perspective, this study reveals the spatial characteristics of PM_{2.5} concentrations and the factors influencing them at the city level in 2000, 2010, and 2018. Global and local spatial autocorrelation tests reveal that land-grant area shows a spatial aggregation pattern and that the main types of spatial aggregation at high-high and low-low indicate the spatial association of PM_{2.5} concentrations between neighboring cities. The global regressions show that carbon emissions, industrial structure, Land transfer, and PM_{2.5} have statistically significant spatial correlations, and their influence relationships are that industrial structure is higher than Land transfer, Land transfer are higher than foreign trade openness, and foreign trade openness is higher than carbon emissions. In contrast, the urbanization rate and GDP do not have a statistically significant effect. In addition, local regressions show that the impact of these influences on Land transfer varies across cities, exhibiting significant spatial heterogeneity.

3: The results of the MGWR model are substantially better than those of the previous GWR and SGWR models, and are more suitable for studying the influence of atmospheric dust particles. However, there are two shortcomings in this paper: (1) due to data limitations, specific variables that directly generate PM_{2.5} dust particles are not included, so the effects of these factors cannot be discussed specifically. (2) Because the MGWR model is so computationally intensive that it cannot be regressed for all samples, this study uses the average PM_{2.5} concentration data, which is more idealized. In the future, it is hoped that the regression can be performed for the entire sample by improving the calculation method and the computer performance.

5.2 Policies and recommendations

In response to these findings, this paper makes the following three policy recommendations.

(1) Frequently Land transfer driving economic urbanization causing more PM_{2.5} pollution, the development model of economic urbanization needs to be changed as much as possible. Change to an intensive, structurally balanced, low-pollution, and technologically progressive development mode, adjust the industrial structure and focus on the speed of economic growth. In terms of land urbanization development, we should make effective use of existing land resources and choose suitable vegetation schemes to effectively purify the air and beautify the urban environment.

(2) The focus of PM_{2.5} pollution prevention policies varies according to the level of urban development. Therefore, to reduce PM_{2.5} pollution in the process of urbanization, attention should be paid to the rational development of industrial structure and appropriate control of the rough expansion of the secondary industry, and cities should reasonably optimize their industrial structure according to their actual situation and appropriately control industries that produce more particulate dust.

(3) Since there are interactions between four factors, namely Land transfer, industrial structure, openness to foreign trade, and carbon emissions, these four factors need to be considered simultaneously to reduce PM_{2.5} pollution in the urbanization process, while also taking into account the appropriate rate of economic development and the four factors.

References

1. Menon JS, Nagendra SMS. Personal exposure to fine particulate matter concentrations in central business district of a tropical coastal city. *J Air Waste Manag Assoc.* 2018 May 4;68(5):415–29.
2. Li Y, Duan J, Yang M, Li Y, Jing L, Yu Y, et al. Transcriptomic analyses of human bronchial epithelial cells BEAS-2B exposed to atmospheric fine particulate matter PM_{2.5}. *Toxicol In Vitro.* 2017 Aug;42:171–81.
3. Badyda AJ, Grellier J, Dąbrowiecki P. Ambient PM_{2.5} Exposure and Mortality Due to Lung Cancer and Cardiopulmonary Diseases in Polish Cities. In: Pokorski M, editor. *Respiratory Treatment and Prevention* [Internet]. Cham: Springer International Publishing; 2016 [cited 2021 Sep 24]. p. 9–17. (Advances in Experimental Medicine and Biology; vol. 944). Available from: http://link.springer.com/10.1007/5584_2016_55
4. Zhang H, Wang S, Hao J, Wang X, Wang S, Chai F, et al. Air pollution and control action in Beijing. *J Clean Prod.* 2016 Jan;112:1519–27.

5. Xue W, Zhang J, Zhong C, Li X, Wei J. Spatiotemporal PM_{2.5} variations and its response to the industrial structure from 2000 to 2018 in the Beijing-Tianjin-Hebei region. *J Clean Prod.* 2021 Jan;279:123742.
6. Du P, Wang J, Niu T, Yang W. PM_{2.5} prediction and related health effects and economic cost assessments in 2020 and 2021: Case studies in Jing-Jin-Ji, China. *Knowl-Based Syst.* 2021 Sep;107487.
7. Song Y, Huang B, He Q, Chen B, Wei J, Mahmood R. Dynamic assessment of PM_{2.5} exposure and health risk using remote sensing and geo-spatial big data. *Environ Pollut.* 2019 Oct;253:288–96.
8. Wang H, Shen X, Liu J, Wu C, Gao J, Zhang Z, et al. The effect of exposure time and concentration of airborne PM_{2.5} on lung injury in mice: A transcriptome analysis. *Redox Biol.* 2019 Sep;26:101264.
9. Gupta J, Vegelin C. Sustainable development goals and inclusive development. *Int Environ Agreem Polit Law Econ.* 2016 Jun;16(3):433–48.
10. Zhang W, Wang MY. Spatial-temporal characteristics and determinants of land urbanization quality in China: Evidence from 285 prefecture-level cities. *Sustain Cities Soc.* 2018 Apr;38:70–9.
11. Fan X, Liu J, Chen J, Zhao L, Hong W. Changes of Land Use and Functions of EcosystemService: A Case Study in China. *Pol J Environ Stud.* 2018 Nov 20;28(1):73–82.
12. Dongliang Z. Farmers Are Growing Further and Further from the Land: Land Transfer and the Practice of Three Rights Separation in China. *Soc Sci China.* 2021 Apr 3;42(2):24–43.
13. Liu K, Lin B. Research on influencing factors of environmental pollution in China: A spatial econometric analysis. *J Clean Prod.* 2019 Jan;206:356–64.
14. Fan W, Hao Y. An empirical research on the relationship amongst renewable energy consumption, economic growth and foreign direct investment in China. *Renew Energy.* 2020 Feb;146:598–609.
15. Lim C-H, Ryu J, Choi Y, Jeon SW, Lee W-K. Understanding global PM_{2.5} concentrations and their drivers in recent decades (1998–2016). *Environ Int.* 2020 Nov;144:106011.
16. Zhang Q, Zheng Y, Tong D, Shao M, Wang S, Zhang Y, et al. Drivers of improved PM_{2.5} air quality in China from 2013 to 2017. *Proc Natl Acad Sci.* 2019 Dec 3;116(49):24463–9.
17. Luo X, Sun K, Li L, Wu S, Yan D, Fu X, et al. Impacts of urbanization process on PM_{2.5} pollution in “2+26” cities. *J Clean Prod.* 2021 Feb;284:124761.
18. Xu G, Ren X, Xiong K, Li L, Bi X, Wu Q. Analysis of the driving factors of PM_{2.5} concentration in the air: A case study of the Yangtze River Delta, China. *Ecol Indic.* 2020

Mar;110:105889.

19. Wu J, Zheng H, Zhe F, Xie W, Song J. Study on the relationship between urbanization and fine particulate matter (PM_{2.5}) concentration and its implication in China. *J Clean Prod.* 2018 May;182:872–82.

20. Ren H, Shang Y, Zhang S. Measuring the spatiotemporal variations of vegetation net primary productivity in Inner Mongolia using spatial autocorrelation. *Ecol Indic.* 2020 May;112:106108.

21. Rossi RE, Mulla DJ, Journel AG, Franz EH. Geostatistical Tools for Modeling and Interpreting Ecological Spatial Dependence. *Ecol Monogr.* 1992 Jun;62(2):277–314.

22. Liu J, Nijkamp P, Huang X, Lin D. Urban livability and tourism development in China: Analysis of sustainable development by means of spatial panel data. *Habitat Int.* 2017 Oct;68:99–107.

23. Lee J, Li S. Extending Moran's Index for Measuring Spatiotemporal Clustering of Geographic Events: Extending Moran's Index. *Geogr Anal.* 2017 Jan;49(1):36–57.

24. Fotheringham AS, Yang W, Kang W. Multiscale Geographically Weighted Regression (MGWR). *Ann Am Assoc Geogr.* 2017 Nov 2;107(6):1247–65.

25. Brunson C, Fotheringham S, Charlton M. Geographically weighted regression modelling spatial non-stationarity. :13.

26. Liu H. Generalized Additive Model. :43.

27. Yang Z, Li C, Fang Y. Driving Factors of the Industrial Land Transfer Price Based on a Geographically Weighted Regression Model: Evidence from a Rural Land System Reform Pilot in China. *Land.* 2020 Jan 1;9(1):7.

28. Xie Q, Sun Q. Assessing the impact of FDI on PM_{2.5} concentrations: A nonlinear panel data analysis for emerging economies. *Environ Impact Assess Rev.* 2020 Jan;80:106314.

29. Cui L, Li R, Song M, Zhu L. Can China achieve its 2030 energy development targets by fulfilling carbon intensity reduction commitments? *Energy Econ.* 2019 Sep;83:61–73.

30. Lin W, Huang J. Impacts of agricultural incentive policies on land rental prices: New evidence from China. *Food Policy.* 2021 Oct;104:102125.

31. Wu Y, Mo Z, Peng Y, Skitmore M. Market-driven land nationalization in China: A new system for the capitalization of rural homesteads. *Land Use Policy.* 2018 Jan;70:559–69.

32. Tong D, Wang X, Wu L, Zhao N. Land ownership and the likelihood of land development at the urban fringe: The case of Shenzhen, China. *Habitat Int.* 2018 Mar;73:43–52.

33. Fan X, Qiu S, Sun Y. Land finance dependence and urban land marketization in China:

The perspective of strategic choice of local governments on land transfer. *Land Use Policy*. 2020 Dec;99:105023.

34. Gao J, Song G, Sun X. Does labor migration affect rural land transfer? Evidence from China. *Land Use Policy*. 2020 Dec;99:105096.

35. Xu D, Yong Z, Deng X, Zhuang L, Qing C. Rural-Urban Migration and its Effect on Land Transfer in Rural China. *Land*. 2020 Mar 11;9(3):81.

36. Shu C, Xie H, Jiang J, Chen Q. Is Urban Land Development Driven by Economic Development or Fiscal Revenue Stimuli in China? *Land Use Policy*. 2018 Sep;77:107–15.

37. Zhou Y, Li X, Liu Y. Land use change and driving factors in rural China during the period 1995-2015. *Land Use Policy*. 2020 Dec;99:105048.

38. Mohammed A, Li Z, Olushola Arowolo A, Su H, Deng X, Najmuddin O, et al. Driving factors of CO₂ emissions and nexus with economic growth, development and human health in the Top Ten emitting countries. *Resour Conserv Recycl*. 2019 Sep;148:157–69.

39. Gryshova I, Kyzym M, Khaustova V, Korneev V, Kramarev H. Assessment of the Industrial Structure and its Influence on Sustainable Economic Development and Quality of Life of the Population of Different World Countries. *Sustainability*. 2020 Mar 8;12(5):2072.

40. Zhang M, Sun X, Wang W. Study on the effect of environmental regulations and industrial structure on haze pollution in China from the dual perspective of independence and linkage. *J Clean Prod*. 2020 May;256:120748.

41. Tan R, Lin B, Liu X. Impacts of eliminating the factor distortions on energy efficiency—A focus on China's secondary industry. *Energy*. 2019 Sep;183:693–701.

42. Fleisher BM, McGuire WH, Wang X, Zhao MQ. Induced innovation: evidence from China's secondary industry. *Appl Econ*. 2021 Jul 5;1–19.

43. Zhu W, Wang M, Zhang B. The effects of urbanization on PM_{2.5} concentrations in China's Yangtze River Economic Belt: New evidence from spatial econometric analysis. *J Clean Prod*. 2019 Dec;239:118065.

44. Liu N, Liu C, Xia Y, Da B. Examining the coordination between urbanization and eco-environment using coupling and spatial analyses: A case study in China. *Ecol Indic*. 2018 Oct;93:1163–75.

45. Wang Q, Jiang R. Is China's economic growth decoupled from carbon emissions? *J Clean Prod*. 2019 Jul;225:1194–208.

46. Zheng J, Mi Z, Coffman D, Milcheva S, Shan Y, Guan D, et al. Regional development and carbon emissions in China. *Energy Econ*. 2019 Jun;81:25–36.

47. Adams S, Acheampong AO. Reducing carbon emissions: The role of renewable energy

and democracy. *J Clean Prod.* 2019 Dec;240:118245.

48. Zheng J, Mi Z, Coffman D, Shan Y, Guan D, Wang S. The Slowdown in China's Carbon Emissions Growth in the New Phase of Economic Development. *One Earth.* 2019 Oct;1(2):240–53.

49. Ma X, Wang C, Dong B, Gu G, Chen R, Li Y, et al. Carbon emissions from energy consumption in China: Its measurement and driving factors. *Sci Total Environ.* 2019 Jan;648:1411–20.

50. Yu S, Zheng S, Li X. The achievement of the carbon emissions peak in China: The role of energy consumption structure optimization. *Energy Econ.* 2018 Aug;74:693–707.

51. Dou Y, Zhao J, Malik MN, Dong K. Assessing the impact of trade openness on CO₂ emissions: Evidence from China-Japan-ROK FTA countries. *J Environ Manage.* 2021 Oct;296:113241.

52. Huang Y, Chen X, Zhu H, Huang C, Tian Z. The Heterogeneous Effects of FDI and Foreign Trade on CO₂ Emissions: Evidence from China. *Math Probl Eng.* 2019 Jan 8;2019:1–14.

53. Kong Q, Peng D, Ni Y, Jiang X, Wang Z. Trade openness and economic growth quality of China: Empirical analysis using ARDL model. *Finance Res Lett.* 2021 Jan;38:101488.

54. Zhang J, Chen T, Fan F, Wang S. Empirical research on time-varying characteristics and efficiency of the Chinese economy and monetary policy: evidence from the MI-TVP-VAR model. *Appl Econ.* 2018 Jul 15;50(33):3596–613.

55. Qiang Q, Jian C. Natural resource endowment, institutional quality and China's regional economic growth. *Resour Policy.* 2020 Jun;66:101644.

56. Huo W, Zhang W, Chen PS-L. Recent development of Chinese port cooperation strategies. *Res Transp Bus Manag.* 2018 Mar;26:67–75.

57. Liang W, Yang M. Urbanization, economic growth and environmental pollution: Evidence from China. *Sustain Comput Inform Syst.* 2019 Mar;21:1–9.

58. Study on Strategy of Human Resources Development in Western China. In: 2018 4th International Conference on Education, Management and Information Technology (ICEMIT 2018) [Internet]. Francis Academic Press; 2018 [cited 2021 Sep 26]. Available from: https://webofproceedings.org/proceedings_series/article/artId/2830.html

59. Jiang J. Can real estate regulatory policies constrain real estate risks to banks? Evidence from China. *J Chin Econ Bus Stud.* 2021 Jan 2;19(1):35–53.

60. Zhang D, Cai J, Liu J, Kutan AM. Real estate investments and financial stability: evidence from regional commercial banks in China. *Eur J Finance.* 2018 Nov 2;24(16):1388–408.

61. Fan Y, Yang Z, Yavas A. Understanding real estate price dynamics: The case of housing

prices in five major cities of China ☆. *J Hous Econ.* 2019 Mar;43:37–55.

62. Feng M, Li DD, Wu S. How Did China Maintain Macroeconomic Stability During 1978–2018? *China World Econ.* 2021 May;29(3):55–82.

63. Zhao Z, Jia H, Chen M. Major Socioeconomic Driving Forces of Improving Population Health in China: 1978–2018. *Popul Dev Rev.* 2020 Dec;46(4):643–76.