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Spatio-Temporal Evolution and Spatial Heterogeneity of Influencing Factors of SO_2 Emissions in Chinese Cities: Fresh Evidence from MGWR

Weipeng Yuan [1,2], Hui Sun [1,2,*], Yu Chen [3] and Xuechao Xia [1,2]

[1] School of Economics and Management, Xinjiang University, Urumqi 830046, China; ywpywp33@163.com (W.Y.); xiaxuechao99@163.com (X.X.)
[2] Center for Innovation Management Research of Xinjiang, Xinjiang University, Urumqi 830046, China
[3] Xinjiang Academy of Social Sciences, Urumqi 830012, China; stevenchen115@163.com
* Correspondence: shui@xju.edu.cn

Abstract: In this study, based on the multi-source nature and humanities data of 270 Chinese cities from 2007 to2018, the spatio-temporal evolution characteristics of SO_2 emissions are revealed by using *Moran's I*, a hot spot analysis, kernel density, and standard deviation ellipse models. The spatial scale heterogeneity of influencing factors is explored by using the multiscale geographically weighted regression model to make the regression results more accurate and reliable. The results show that (1) SO_2 emissions showed spatial clustering characteristics during the study period, decreased by 85.12% through pollution governance, and exhibited spatial heterogeneity of differentiation. (2) The spatial distribution direction of SO_2 emissions' standard deviation ellipse in cities was "northeast–southwest". The gravity center of the SO_2 emissions shifted to the northeast, from Zhumadian City to Zhoukou City in Henan Province. The results of hot spots showed a polarization trend of "clustering hot spots in the north and dispersing cold spots in the south". (3) The MGWR model is more accurate than the OLS and classical GWR regressions. The different spatial bandwidths have a different effect on the identification of influencing factors. There were several main influencing factors on urban SO_2 emissions: the regional innovation and entrepreneurship level, government intervention, and urban precipitation; important factors: population intensity, financial development, and foreign direct investment; secondary factors: industrial structure upgrading and road construction. Based on the above conclusions, this paper explores the spatial heterogeneity of urban SO_2 emissions and their influencing factors, and provides empirical evidence and reference for the precise management of SO_2 emission reduction in "one city, one policy".

Keywords: SO_2 emission; MGWR model; influencing factors; spatial heterogeneity

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1. Introduction

As people's living quality has improved, their pursuit of extravagant material enjoyment has escalated, leading to environmental destruction and pollution. The main type of environmental pollution in China is industrial pollution, and these pollutants are divided into three states: stationary, liquid, and gaseous. Among them, the impact of gaseous pollution on the public is particularly obvious [1–3]. In the winter of 2013, severe haze events impacted many parts of China on a large scale. Since then, air pollution has gradually aroused widespread concern in society. Since the reform and opening up, the rough industrialization development pattern has played an effective role in promoting the development of China's economy. However, as a consequence of excessive resource consumption, China is gradually becoming one of the most polluted countries in the world. In particular, SO_2 has become one of the major pollutants of $PM_{2.5}$ and acid rain [4]. As the "invisible killer" of the "smog incident" in London, England, in 1952, SO_2 has been classified as a Class III carcinogen by the World Health Organization. SO_2 can seriously

damage the health of the public, even killing people due to chest congestion, suffocation, cancer, and traffic accidents [5]. According to the 2018 Global Environmental Performance Index report jointly released by Yale University and Columbia University, China ranked 177th in the world, just ahead of India, Bangladesh and Nepal. In China, as one of the world's largest developing countries, air pollution cannot be ignored.

Fortunately, the rapidly growing SO_2 emissions have attracted extensive attention from all sectors of society. Since China joined the East Asia Acid Deposition Monitoring Network in 1998, increasing attention has been paid to the monitoring of SO_2 emissions and concentrations in the atmosphere. In 2002, the monitoring stations at all levels of China's Environmental Protection Administration (now known as the Ministry of Natural Resources) carried out a general survey of acid rain. In 2007, China's 11th Five-Year Plan linked the environmental protection assessment to the promotion of government officials for the first time. At the same time, a series of important documents, such as the assessment measures for the total emission reduction in major pollutants (GF(2007) No. 36), were issued. In 2012, the Ministry of Environmental Protection (now the Ministry of Natural Resources) formulated and issued a scheme for setting up the national ambient air monitoring network (cities above prefecture level) in the 12th Five-Year Plan (HF(2012) No. 42). Among the national ambient air quality monitoring networks at the national, provincial, municipal, and county levels, SO_2 ranked first in the detection projects of urban air, background air, regional air, and acid rain, which shows that SO_2 is one of the representative pollutants used for evaluating the regional ambient air quality, and that it affects the regional transmission mechanisms of pollutants.

The report of the 19th National Congress of 2017 forwarded the battle of pollution prevention and control, and Premier Li Keqiang also emphasized that the emission of sulfur dioxide, nitrogen oxides, and PM2.5 should be controlled to ensure the "victory of the blue sky defense war" in the same year's "Government Work Report". Therefore, determining the main influencing factors of urban SO_2 emissions has become an urgent task, and this is also a prerequisite for subsequent industrial policy decision making and management optimization.

At present, the research on air pollution mainly focuses on AQI, $PM_{2.5}$, PM_{10}, CO, NO_2, SO_2, and other major pollutants [6,7]. There are a considerable amount of studies on the causes [8], hazards [9], spatio-temporal evolution [10], influencing factors [11], and governance models of air pollution [12]. The influencing factors of air pollution are a comprehensive result of natural and human factors [13]. Natural factors include rainfall, temperature, climate, wind, and terrain, while anthropic factors include the economy, industry, population, technology, policy, culture, and trade. The research data were mainly obtained from statistical yearbooks, satellite remote sensing data inversion, monitoring stations, news media reports, etc. [14]. The evolution of air pollution can be explored based on big data from different time dimensions, such as hourly, weekly, quarterly, and annual perspectives [15].

Some researchers have discussed the impact mechanisms of the COVID-19 pandemic [16], urbanization [17], foreign direct investment [18], climate change [19], carbon emissions trading [20], meteorological conditions [21], and tourism development [22] on air pollution. The results of this research have shown a negative inhibition, positive promotion, or nonlinear effects. In addition, the direct and indirect external influences of urban air pollution on socio-economic development, anthropic activities, and natural ecosystems have also been discussed. For instance, some researchers have also discussed the external effects of urban air pollution on families' economic costs [23], residents' health levels [24], urban crime rates [25], and electricity consumption [26]. Therefore, there may be endogenous causal relationships between air pollution and relevant variables. The same influencing factors may have uncertain effects on SO_2 emissions with multiscale spatial synergy or trade-offs, which results in significant spatial heterogeneity effects. It is necessary to select a suitable research model to effectively identify the robust influencing factors.

In terms of research methods, there are many models used to study the causes of air pollution, such as the Bayesian [27] and spatial econometric models [28], the generalized divisia index approach [29], geographic probes [8], and GWR [30]. Liu et al. used the MGTWR model to infer PM 2.5 at non-sampled points, and applied the posterior uncertainty assessment value to improve the model's accuracy [31]. The reason for this is that the spatial econometric model can avoid spatial autocorrelation and spillover effects compared with the general model, and its regression results are more robust. At the same time, spatial econometric models generally require a large number of microscopic data samples, especially the scale selection of regional research samples. As spatial data, information about regional SO_2 emissions includes a series of location attributes and may cause spatial effects, such as spatial dependence and spatial heterogeneity, which violate the basic assumptions of OLS and cause estimate bias.

The size of the study region's scale determines the reference value of its findings. Large-scale studies provide the framework for regional strategies, medium-scale studies lay the basis for regional planning and cooperation, and small-scale studies determine specific regional responses. The study areas for air pollution research include provinces, cities [32], urban agglomerations, and typical areas of watersheds [28], mainly including Beijing, Shanghai, Guangzhou, Beijing–Tianjin–Hebei, Yellow River Basin, and Yangtze River Basin. It can be seen that the smaller the scale of a regional study, the more precise and specific the regional policy regime will be. Therefore, we use a study sample of 270 cities in China for the regression analysis.

The main innovations of this paper can be described as follows: First, the ArcGIS technologies of *Moran's I*, spatial kernel density, hot spot analysis, and standard deviation ellipse are used to systematically show the evolution characteristics and rules of SO_2 emissions in China's cities. Second, previous studies have mainly focused on provincial-level and single local areas; there are few studies that focus on the city unit in China. Using general regression or classical GWR models may lead to non-robust results. Multiscale geographically weighted regression can reflect the spatially heterogeneous effects of different variables on the dependent variable, and its regression results are more robust and reliable. Therefore, the MGWR model is used to investigate, simultaneously, the spatial heterogeneity effects of natural and anthropic factors on SO_2 emissions, in order to further clarify the causal mechanisms of urban air pollution. Third, the paper further analyzes different dimensions of the heterogeneity, and refines the explanation of the causes of SO_2 emissions, providing new research evidence for the pollution reduction in "one city, one policy" in different countries and regions of the world.

The rest of this article is organized as follows. In Section 2, we mainly describe data sources and research methodology. In Section 3, we analyze spatio-temporal distribution characteristics of SO_2 emissions in Chinese cities. Section 4 is the comparative analysis of the results. Section 5 is conclusions and recommendations.

2. Material and Research Methodology

2.1. Study Area Overview

Limited by the lack of existing data for individual cities, we designed the study area to cover 270 cities in China. Taking 2007 as the starting year for China's environmental protection turning point, we selected the data from 2007 to 2018, and viewed cities as the basic research modules for the formulation and implementation of regional SO_2 pollution prevention policies. The study area is shown in Figure 1.

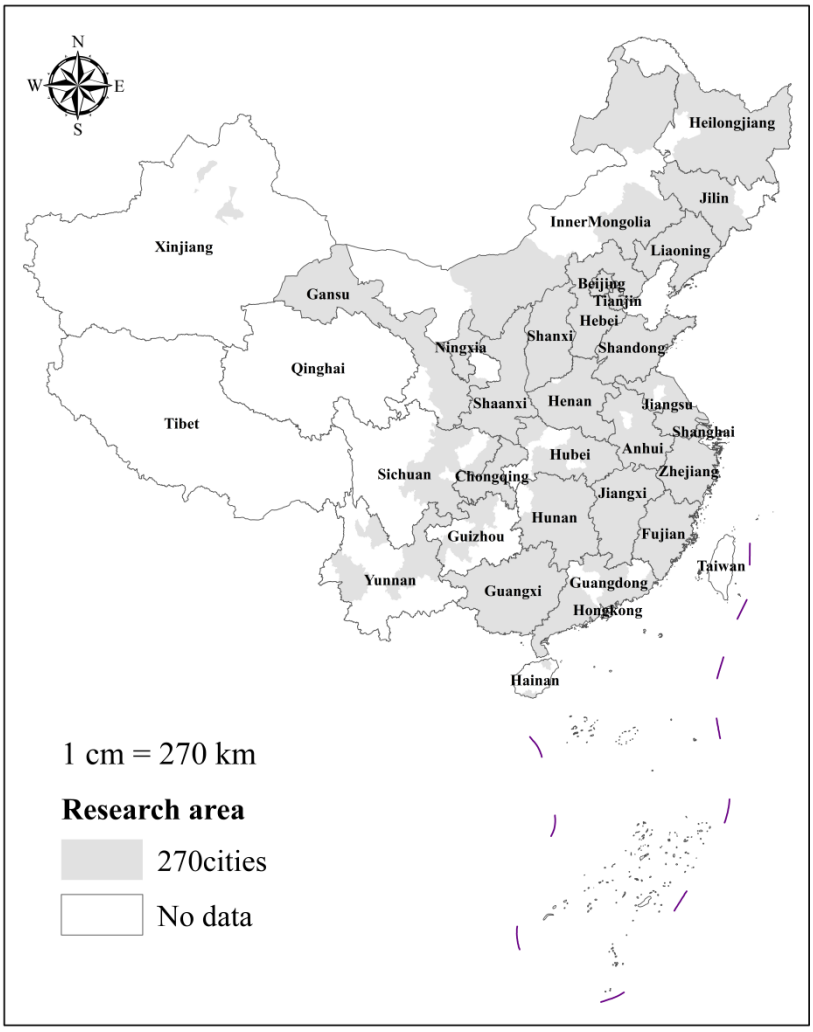


Figure 1. Geographical location of 270 urban study areas in China. Note: Based on the standard base map of the standard map service system of the Ministry of Natural Resources (review number: GS (2016)1569), the base map was not modified (the same below).

2.2. Data Sources and Variable Selection

The explained variable was urban SO_2 emissions, and the data on industrial SO_2 emissions from prefecture-level cities in China were extracted from the 2019 China City Statistical Yearbook. Total industrial sulfur dioxide emissions in China were 4.47 million tons in 2018, declining 79.11% compared to 2007.

Air pollution is not determined by a single factor; it is the result of the joint action of socio-economic and natural conditions. Urban precipitation, ventilation coefficient, topography of urban terrain may influence SO_2 emissions through the complex energy flows and material cycles in the ecosystem [33]. Obviously, human activities can generate SO_2 through resource development, utilization, and consumption on the one hand, and can control SO_2 pollution through environmental policies, technological innovation, and afforestation on the other [34].

Based on the pollution refuge hypothesis, Porter effect, environmental externality, Environmental Kuznets Curve, industrial structures, and the ecosystem, the natural and socioeconomic influencing factors could be fully considered [32]. The explanatory variables selected for this paper were urban precipitation (UP), ventilation coefficient (VC), topography of urban terrain (UT), per capita urban GDP (PGDP), population intensity (PI), the regional innovation and entrepreneurship level (RIE), foreign direct investment (FDI), financial development (FD), upgrading of industrial structures (UIS), research development

investment (R&D), road construction (RC), and government intervention (GI). By selecting socio-economic and natural indicators, we aimed to explore the main factors affecting SO_2 emission.

The indicators data of socio-economic data mainly obtained from the 2008 and 2019 China City Statistical Yearbook by calculation, were compiled by the National Bureau of Statistics of China and Statistical Bureau of each prefecture-level city. The calculation process is shown in Table 1. The data for the regional innovation and entrepreneurship level (RIE) were obtained from the Report of China Regional Innovation and Entrepreneurship Development Index by the National Development Research Institute of Peking University. Urban precipitation data (UP) were extracted from precipitation monitoring stations from the China Meteorological Data Network. Ventilation coefficient (VC) data were obtained from the product of wind speed and the atmospheric boundary layer height. Based on the ERA-interim database provided by the European center for medium-range weather forecasts (ECMWF), the raster data of prefecture-level cities in China were constructed. The indicator of topography of urban terrain(UT) was measured using GIS technology to extract a 1KM × 1KM raster at 1:1 million scale of China's geographic digital elevation simulation data. See Table 1 for descriptive statistics involving the variables.

Table 1. Variable description and index design.

Variables	Variable Description	Unit	Source of Original Data
Sulfur dioxide emissions	Urban Industrial sulfur dioxide emissions	10^7 Kg	China City Statistical Yearbook
Foreign direct investment	City foreign investment utilization level	Billions of dollars	China City Statistical Yearbook
Regional innovation and entrepreneurship level	China Regional Innovation and Entrepreneurship Index	Points	Report of China Regional Innovation and Entrepreneurship Development Index by the National Development Research Institute of Peking University
Population intensity	Year-end population per unit area	People per square kilometer	China City Statistical Yearbook
Financial development	Loan balance as a percentage of GDP by city	%	China City Statistical Yearbook
Per capita urban GDP	GDP per capita at constant prices in the starting year	CNY	China City Statistical Yearbook
Urban precipitation	Average annual urban precipitation	MM	China Meteorological Data Network
Ventilation coefficient	Urban air circulation level	10^3 m^2/s	European Centre for Medium-Range Weather Forecasts
Upgrading of industrial structure	Ratio of tertiary sector to secondary sector	%	China City Statistical Yearbook
Research development investment	Urban Science and Technology Expenditure	10^8 CNY	China City Statistical Yearbook
Road construction level	Number of urban road miles	Kilometers	Statistical Bureau of each prefecture-level city
Topography of urban terrain	Average urban topographic elevation	M	Global Change Science Research Data System
Government intervention	Public Finance Expenditure	10^8 CNY	China City Statistical Yearbook

2.3. Data Description

For some of the missing data, we calculated the missing values using linear interpolation. The relevant variable definitions are shown in Table 2.

Table 2. Variable description.

Variables	English Abbreviation	N	Mean	Sd
Sulfur dioxide emissions	SO_2	540	43,902.59	55,306.68
Foreign direct investment	FDI	540	51,559.09	167,507.74
Regional innovation and entrepreneurship level	RIE	540	52.57	28.48
Population intensity	PI	540	431.31	338.78
Financial development	FD	540	57.59	69.38
Per capita urban GDP	PGDP	540	30,775.70	39,450.51
Urban precipitation	UP	540	10,061.61	5163.57
Ventilation coefficient	VC	540	1638.56	481.73
Upgrading of Industrial structure	UIS	540	71.983	62.65
Research development investment	R&D	540	95,925.20	384,415.35
Road construction level	RC	540	11,737.555	7085.34
Topography of urban terrain	UT	540	0.66	0.73
Government intervention	GI	540	3,313,888.80	6,487,643.30

Note: English abbreviation: the variables in the following table are abbreviations.

2.4. Research Methodology

In this section, *Moran's I* was used to represent the global agglomeration degree of SO_2 emissions. Spatial kernel density was used to characterize the point aggregation degree of SO_2 emissions. Hot spot analysis was used to characterize the local concentration of SO_2 emissions. The standard deviation ellipse was used to represent the azimuth deviation of the spatial distribution of SO_2 emissions. Through the above methods, we were able to reveal the spatial distribution and temporal and spatial evolution characteristics of SO_2 emissions.

2.4.1. Spatial Autocorrelation

Waldo Tobler's first law of geography is the spatial dependence of "proximity and similarity": the closer the spatial distance, the stronger the correlation between elements. Spatial autocorrelation is often expressed by *Moran's I*, Geary's C, and Getis-Ord G_i*. Global *Moran's I* was derived from the Pearson correlation. Positive values indicate positive spatial autocorrelation, while negative values indicate negative spatial autocorrelation, and the value range is between [–1, 1]. The calculation was designed as follows:

$$Moran's\ I = \frac{n}{\sum_i \sum_j w_{ij}} \times \frac{\sum_i \sum_j w_{ij}(x_i - \overline{x})(x_j - \overline{x})}{\sum_j (x_i - \overline{x})^2} \quad (1)$$

n is the sample size, w_{ij} is the spatial weight matrix using inverse distance weights; x_i and x_j are the observations of spatial units i and j, $\overline{x}$ is the average of the observations.

2.4.2. Spatial Kernel Density

Kernel density visualizes spatial aggregation by measuring the density of spatial elements within its periphery. The equation can be expressed as follows:

$$f_n(x) = \frac{1}{nh} \sum_{i=1}^{n} k\left(\frac{x - x_i}{h}\right) \quad (2)$$

$f_n(x)$ is the kernel density value at the x point; k is the kernel function; h is the bandwidth; $x - x_i$ is the distance from the estimated point x to sample x_i.

2.4.3. Hot Spot Analysis

We used the high and low value area statistics of hot spot analysis (Getis-Ord G_i*) to measure the local agglomeration of cold–hot spots in the spatial distribution of urban SO_2 emissions. The hot spot analysis could be estimated by the following equation:

$$G_i^*(d) = \sum_{j=1}^{n} W_{ij}(d)X_j \Big/ \sum_{j=1}^{n} X_j \tag{3}$$

$$Z(G_i^*) = [G_i^* - E(G_i^*)] \Big/ \sqrt{VAR(G_i^*)} \tag{4}$$

In the equation, $G_i^*(d)$ is the statistic of each spatial unit i based on spatial distance weights $w_{ij}(d)$, $Z(G_i^*)$ is the standardized statistic of the $G_i^*(d)$ test; if the value is significantly positive, it indicates a hot spot agglomeration area, and the opposite is a cold spot agglomeration area. X_j is the attribute values of spatial cells j; $E(G_i^*)$ and $VAR(G_i^*)$ are the mathematical expectation and coefficient of variation $G_i^*(d)$, respectively.

2.4.4. Standard Deviational Ellipse (SDE)

The evolutionary characteristics of geographic elements in two-dimensional spatial patterns were quantitatively revealed through the changing patterns of standard deviation ellipses. The process could be expressed by the following equation:

$$\overline{X} = \frac{\sum_{i=1}^{n} W_i X_i}{\sum_{i=1}^{n} W_i}; \overline{Y} = \frac{\sum_{i=1}^{n} W_i Y_i}{\sum_{i=1}^{n} W_i} \tag{5}$$

$$\sigma_x = \sqrt{\frac{\sum_{i=1}^{n} \left(w_i \widetilde{x}_i \cos\theta - w_i \widetilde{y}_i \sin\theta\right)^2}{\sum_{i=1}^{n} w_i^2}} \tag{6}$$

$$\sigma_y = \sqrt{\frac{\sum_{i=1}^{n} \left(w_i \widetilde{x}_i \sin\theta - w_i \widetilde{y}_i \cos\theta\right)^2}{\sum_{i=1}^{n} w_i^2}} \tag{7}$$

(x_i, y_i) is the latitude and longitude of the geographic center of the city; w_i is the attribute value of each city's economic factors; $(\overline{x}_w, \overline{y}_w)$ is the weighted mean center; σ_x and σ_y are the standard deviations of the x and y axes, respectively.

2.4.5. Multiscale Geographically Weighted Regression Model (MGWR)

Multiscale geographically weighted regression (MGWR) was developed by Professor Stewart Fotheringham's team [35,36]. The second law of geography assumes that spatial segregation causes the spatial localization and stratified heterogeneity of the study object. In this paper, we applied the multiscale geographically weighted regression model to explore the spatial heterogeneity of factors influencing SO_2 emissions. The multiscale geographically weighted regression model could be estimated by the following equation:

$$y_i = \sum_{j=1}^{k} \beta_{bwj}(u_i, v_i)x_{ij} + \beta_0(u_i, v_i) + \varepsilon_i \tag{8}$$

bwj represents the elasticity bandwidth of the regression coefficient of the variable j; (u_i, v_i) is the central coordinate of the i city location; $\beta_0(u_i, v_i)$ and ε_i denote the intercept term and error term of the model, respectively. The impact factor coefficients β of the MGWR model were obtained based on the bandwidth of data differentiation, which was an improvement over the fixed bandwidth of classical GWR. In addition, the MGWR model uses the classical GWR quadratic kernel function and the AICc criterion to judge the degree of fit of the regression results.

Classical GWR is based on the weighted least squares estimation method, which is defined by the generalized additive linear model (GAM) [37]. In this paper, the initialization was based on the classical GWR estimation, which was fitted by the initialized residuals $\hat{\varepsilon}$ between the initially estimated predicted value and the true value.

$$\hat{\varepsilon} = y - \sum_{j=1}^{k} \hat{f}_j (f_j = \beta_{bwj} x_j) \tag{9}$$

(1) Classical GWR regression was conducted by residuals $\hat{\varepsilon}$ plus the first additive term $\hat{f}_1$ and the first independent variable x_1, which matched the best-fit bandwidth bw_1 to obtain new residual $\hat{\varepsilon}$ and parameters $\hat{f}_1$ to replace the original estimate. (2) The residual $\hat{\varepsilon}$ and $\hat{f}_2$ of the second variable were replaced by regression of the new residuals plus the second additive term $\hat{f}_2$ and the second independent variable x_2. (3) Repeated as above up for the last variable x_k (assuming k variables). (4) The above steps were a complete cycle, repeating the estimation until they reached the convergence criterion.

In this paper, the classical residual sum-of-squares variation ratio (*RRS*) was used as the convergence criterion. The equation could be expressed as follows:

$$SOC_{RSS} = \left| \frac{RSS_2 - RSS_1}{RSS_2} \right| \tag{10}$$

RSS_1 indicates the sum of squared residuals from the previous step; RSS_2 indicates the sum of squared current residuals.

The metering software was MGWR2.2, downloaded from the School of Geosciences and Urban Planning at Arizona State University (https://sgsup.asu.edu/sparc/mgwr, accessed on 29 October 2021).

3. Results

3.1. Spatio-Temporal Evolution Distribution of SO_2 Emissions

Figure 2 shows global *Moran's I* of SO_2 emissions in 270 Chinese cities in 2007 and 2018. By using the rook neighboring spatial matrix weights of GeoDa-1.18 software, the results showed that *Moran's I* of SO_2 emissions in 2007 and 2018 were 0.062 and 0.306, and the p-values for both were significantly positive at the level of 1%. Therefore, there were significant aggregation effect characteristics and a significant global autocorrelation of the SO_2 emissions.

As shown in Figure 3, under the same reference concentration index, the total amount of SO_2 pollution emissions from the 270 Chinese cities showed a declining trend from 2007 to 2018, and the spatial diffusion breadth and scale of the overall pollution emissions shrank. The average SO_2 emissions reduced by 85.12% from 68,595,730 kg in 2007 to 10,209,440 kg in 2018. During the study period, SO_2 emissions in the studied Chinese cities showed a spatial evolution feature from " fragmentation of high emission" to "sporadic prominence of low emission ". Compared with 2018, most cities in China had higher SO_2 emissions in 2007, such as Zhuhai (Guangdong province), Weifang (Shandong province), and Henan–Hengyang, and all of them exceeded 300,000,000 kg. There were 85 cities that discharged more than 80,000,000 kg, accounting for 31.48% of the total cities. In 2018, cities with SO_2 emissions below 20,000,000 kg accounted for 67.41% of this total. As a result of the layouts of industries such as the steel and chemical industries, the SO_2 emissions of Tangshan (Hebei province), Chongqing, Suzhou (Jiangsu province), and Weinan (Shaanxi province) cities all exceeded 80,000,000 kg. Due to the spatial patterns of emission changes, many cities of Shaanxi, Shandong, Zhejiang, Hunan, Yunnan, and Henan showed obvious emission reduction effects, but the SO_2 emissions of some cities, such as Tangshan (Hebei province), Anshan (Liaoning province), Yuncheng (Shanxi province), Binzhou (Shandong province), Erdos, Baotou (Inner Mongolia), Wuxi (Jiangsu province), and Jiangmen (Guangdong province) had increased by more than 30,000,000 kg, showing a trend of increasing sporadic emissions that requires focused supervision and treatment.

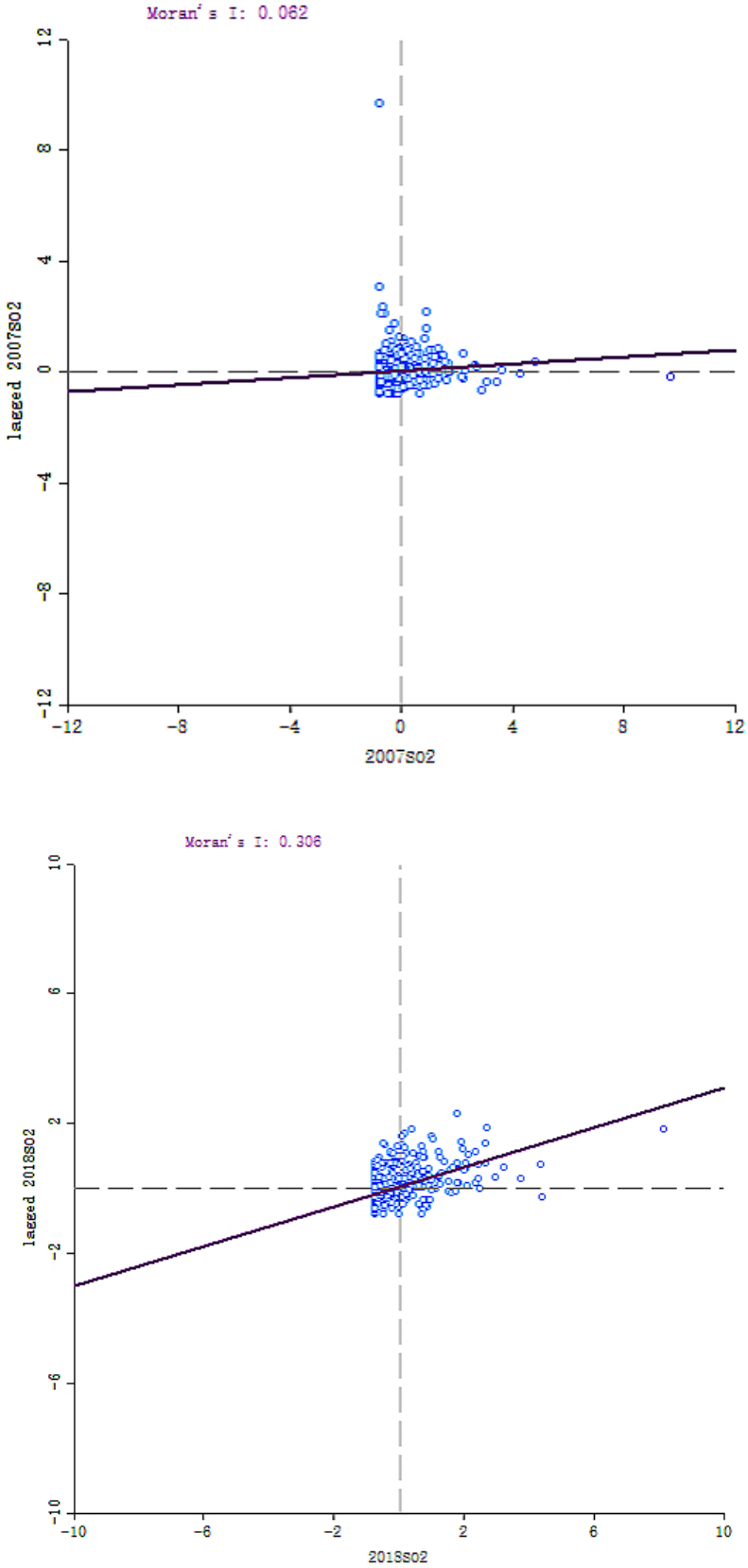
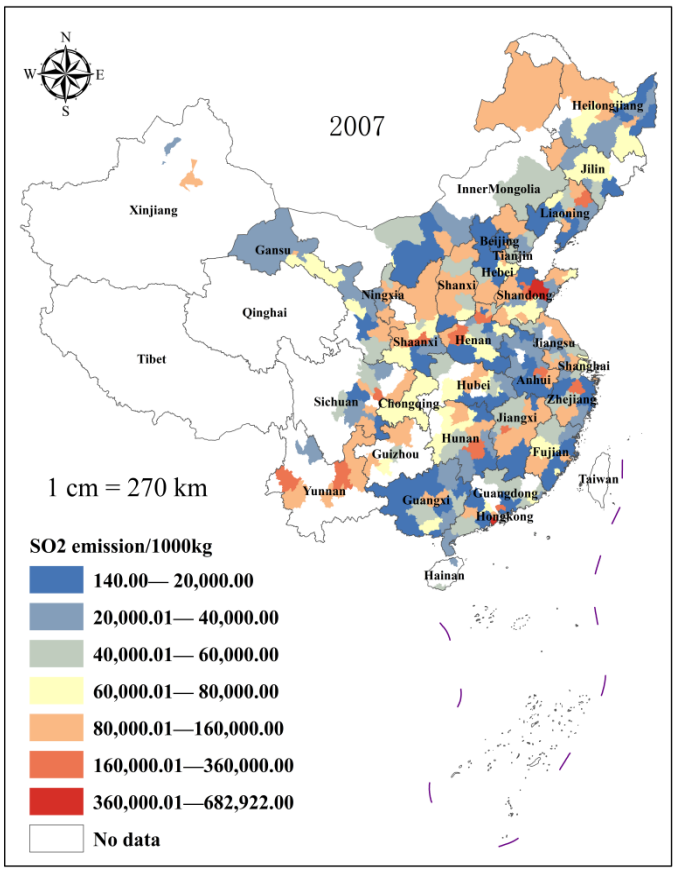


Figure 2. *Moran's I* of industrial SO_2 emissions of 270 cities in 2007 and2018.



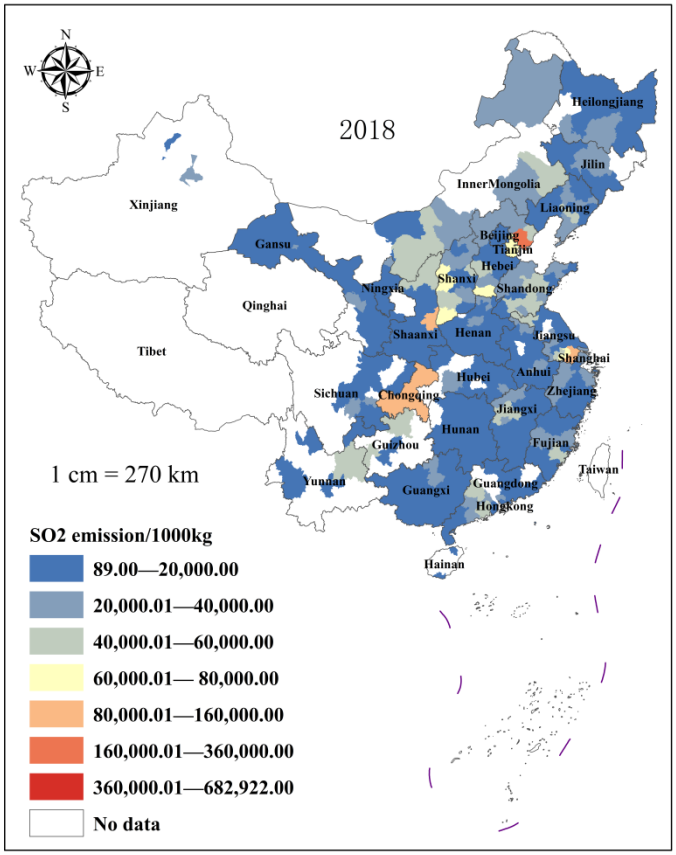


Figure 3. *Cont*.

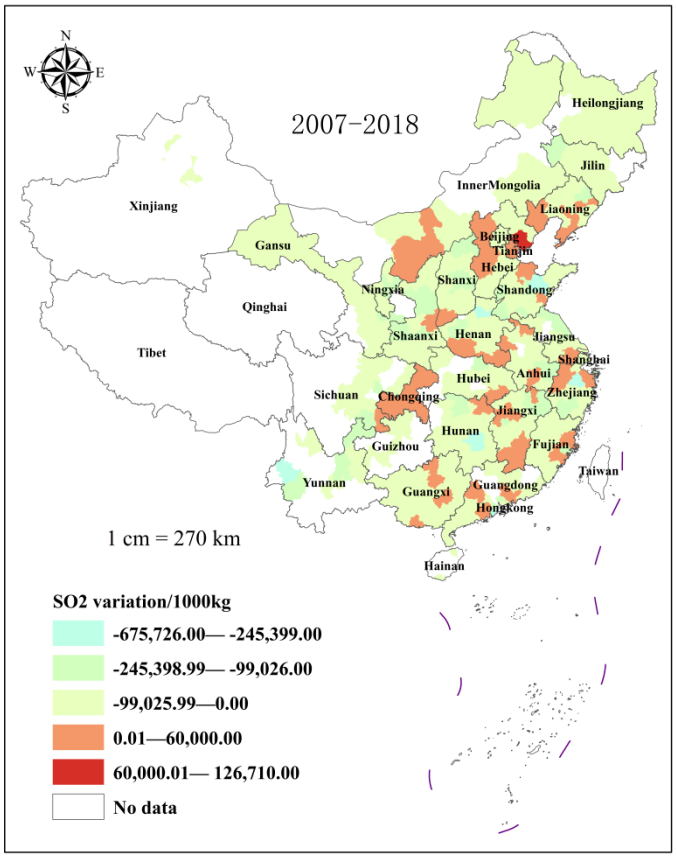


Figure 3. Spatio-temporal evolution of SO_2 emissions in 270 cities in 2007 to 2018.

3.2. Spatio-Temporal Clustering Characteristics of SO_2 Emissions

We selected 2007 and 2018 as the study time points and used ArcGIS10.3 technology and the kernel density analysis method in the Spatial Analyst tool to extract urban surface elements as point elements.

During the study period, the spatial density of SO_2 emissions decreased significantly, but the spatial layout changed little and remained consistent with the spatial distribution of SO_2 emissions. Through a spatial kernel density analysis, the key control areas of SO_2 emissions became obvious. The high-density areas of SO_2 emissions in 2007 were mainly located in cities in Liaoning, Shandong, Shanxi, Henan, Shaanxi, Jiangsu, Anhui, Zhejiang, Jiangxi, Hubei, Hunan, Sichuan, Yunnan, and Guangdong provinces. The spatial density interval of SO_2 emissions ranged from 0 to 40.32. In 2018, the high-density areas were distributed in cities in Liaoning, Hebei, Shandong, Shanxi, Henan, Jiangsu, Anhui, Zhejiang, Jiangxi, Chongqing, Guizhou, and Guangdong. The spatial density interval of SO_2 emission ranged from 0 to 9.17. From the perspective of north–south geographical distribution, cities in the north were relatively contiguous and cities in the south were relatively scattered (see Figure 4).

The ArcGIS 10.3 software was used to perform the geographic distribution metrics and cluster distribution mapping of SO_2 emissions through the standard deviation ellipse and hot spot analysis, respectively. The results of the standard deviation ellipse showed that the spatial distribution of SO_2 emissions presented the "northeast–southwest" direction. From 2007 to 2018, the geographic distribution center of urban SO_2 emissions moved in the northeast direction, from Zhumadian to Zhoukou in Henan Province. Further, the agglomeration effect of SO_2 emissions became larger.

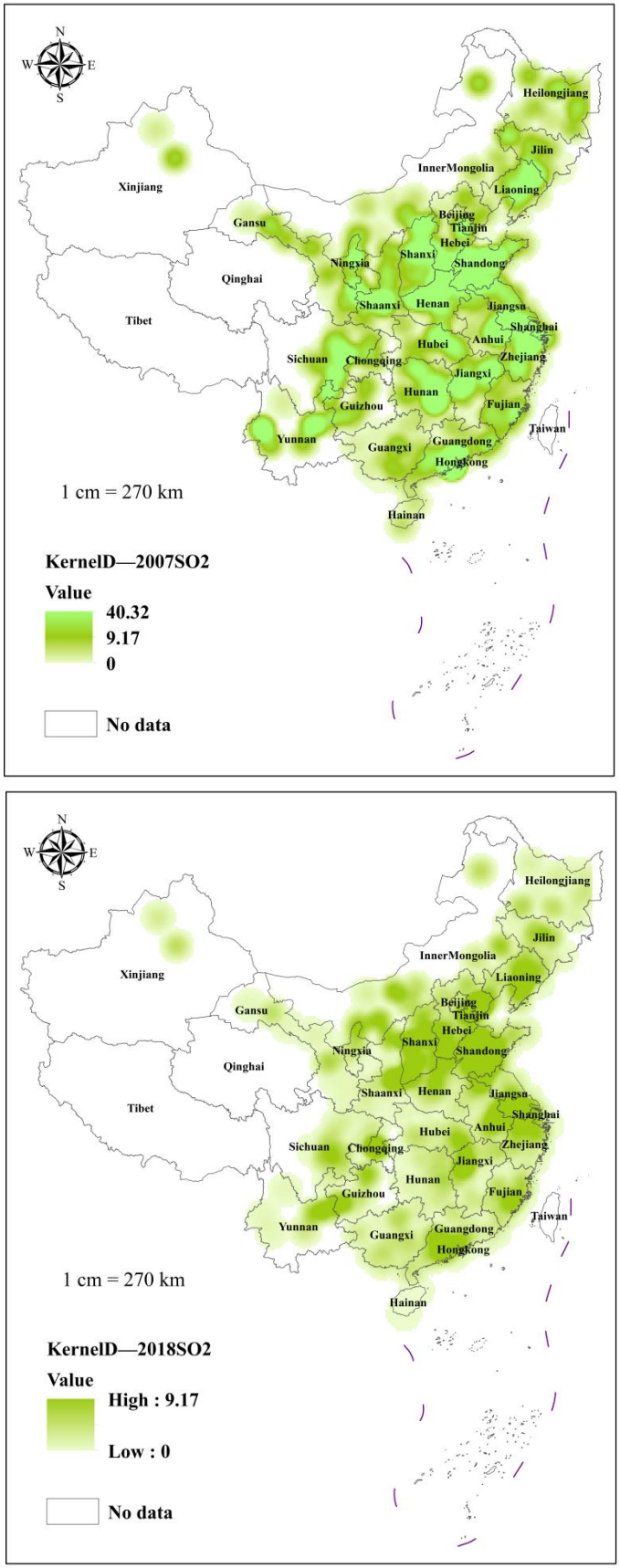


Figure 4. Spatio-temporal evolution of SO_2 emissions in 270 cities in 2007 and 2018.

The results of the hot spot analysis showed that the hot spots and cold spots of SO_2 emissions in the Chinese cities increased, and the hot spots gradually shifted from some sporadic cities in Shanxi, Hebei, and Yunnan to contiguous cities in Beijing, Tianjin, Hebei, Shanxi, Shandong, Inner Mongolia, and Jiangsu; the cold spots shifted from some cites in "Guangxi, Anhui" to contiguous cities in "Hubei, Gansu", showing a polarization trend of "northern hot spots gathering, southern cold spots scattered", which indicatedthat SO_2 emissions of northern cities in China were in the development period of the differentiative effect(see Figure 5).

3.3. Analysis of Model Indicators

The previous paper introduced the variation pattern of SO_2 emissions from spatial and temporal distribution and evolution. In this paper, we analyzed the influencing factors affecting SO_2 emissions by comparing the advantages and disadvantages of the OLS, GWR, and MGWR models and selecting the appropriate model.

The results in Table 3 show that the regression results of MGWR were better than those of OLS and classical GWR. The sum of residual squares and the AICc value of the MGWR model test were smaller, while the goodness of R^2 value was larger. The Akaike Information Criterion(AIC) or Akaike Information Criterion Corrected(AICc) and R^2 value are a common standard used to judge the goodness of fit of regression models. The smaller the AIC and AICc value, the higher the R^2 value and, thus, the higher the fitting degree of the model.

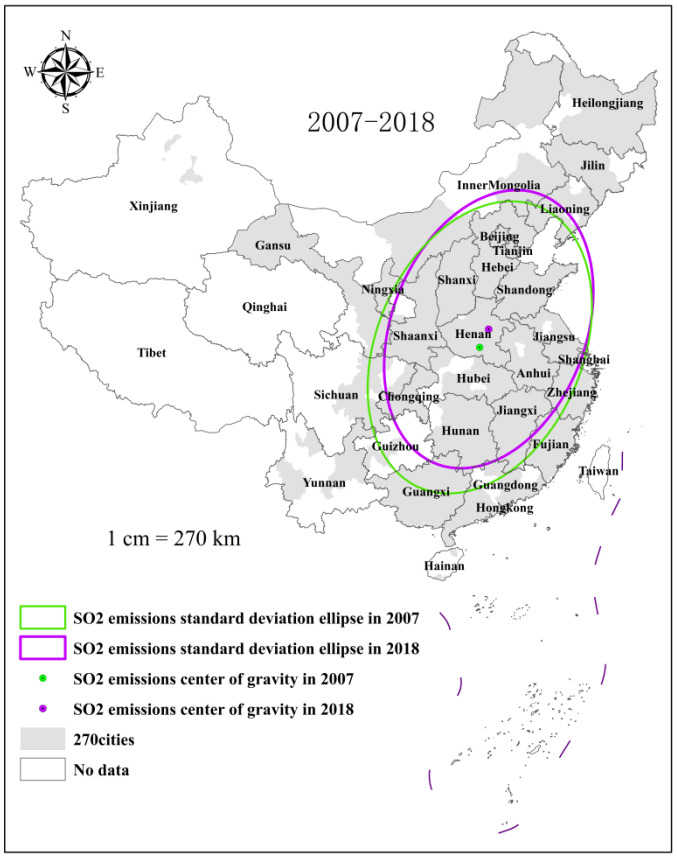


Figure 5. *Cont.*

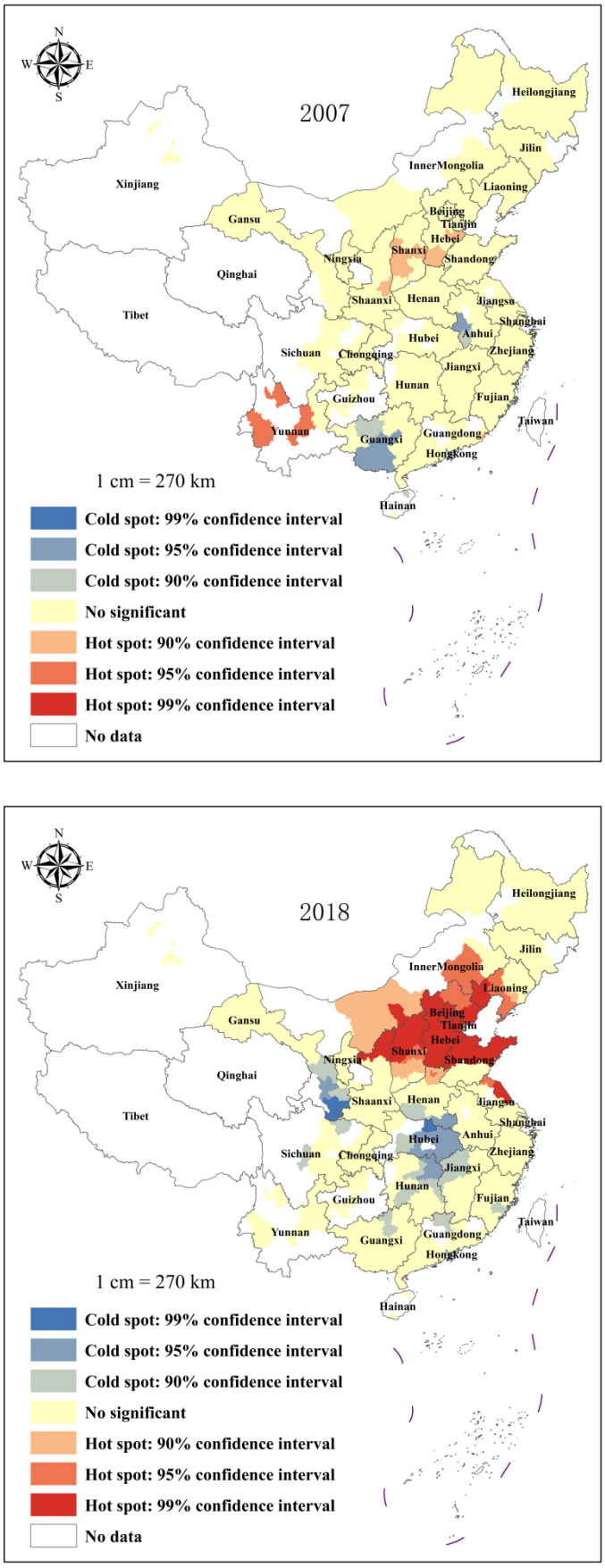


Figure 5. Spatio-temporal evolution and hot spots of SO_2 emissions in 270 cities in 2007 and 2018.

Table 3. Comparison of OLS, Classic GWR, and MGWR fitting results.

Model Metrics	SO_2					
	2007			2018		
	OLS	Classic GWR	MGWR	OLS	Classic GWR	MGWR
Residual Sum of Squares	276.680	231.103	146.813	47.637	197.944	138.147
AICc	793.222	756.115	678.899	148.480	714.299	690.003
Goodness of fit R^2	0.128	0.144	0.456	0.262	0.267	0.488
Variable	Bandwidth					
Constants			269			269
FDI			267			269
RIE			269			266
PI			269			269
FD			266			267
PGDP			185			269
UP	No	150	269	No	269	269
VT			90			269
UIS			269			219
R&D			67			269
RC			269			196
UT			269			43
GI			113			224

According to the endowment characteristics of data, bandwidth selection showed spatial heterogeneity. The larger the bandwidth of the influencing factor, the stronger the applicability of the whole spatial scale. On the contrary, the smaller the bandwidth, the stronger the heterogeneity of the variable spatial scale. However, classical GWR has a fixed bandwidth value, which can only reflect the influence degree of the factor at the average spatial scale, which leads to estimation deviation with regard to the influencing factors. The MGWR model can automatically set different bandwidth values according to the characteristics of variables, which can fully reflect the spatial heterogeneity of influencing factors. Thereby, the MGWR model outperformed OLS and classical GWR. The following section analyzed the results from specific regressions.

3.4. Time-Series Analysis of Influencing Factors in Average Scale

From the results of the OLS method and the classic GWR model in Table 4, it can be concluded that the regression results of the factors were differential because the regression method used was different, and the classic GWR model was better than the OLS method. Comparing the results of classical GWR regressions from 2007 to2018 in the average spatial scale, the effectiveness of SO_2 reduction was mainly the result of economic and social factors. As the urban per capita GDP grew, SO_2 emissions declined year by year, but the impact has not been significant.

In 2007, in the average spatial scale, the influencing factors of SO_2 emission reduction were industrial structure upgrading and government interventions. Further, the influencing factors of the increase in SO_2 emissions in 2007 were foreign direct investment and research development investment. In 2018, the factors influencing the reduction in SO_2 emissions were research development investment, population intensity, foreign direct investment, urban precipitation, and industrial structure upgrading, while the factors influencing the increase in SO_2 emissions were government intervention and the regional innovation and entrepreneurship level. Therefore, the influencing factors of SO_2 emissions at different time points differed, and the degree and direction of influence could change.

Table 4. Results comparison of the average spatial scale model.

Variables	English Abbreviation	SO_2 (OLS)		SO_2 (GWR)	
		2007	2018	2007	2018
Constant term	Intercept	12.909 ***	−24.298	0.000	0.000
Foreign direct investment	FDI	0.042	−0.088	0.113 *	−0.204 * (↓)
Regional innovation and entrepreneurship level	RIE	−0.056	1.298	0.112	0.428 *** (↑)
Population Intensity	PI	0.227 **	0.14 (↓)	−0.008	−0.232 *** (↑)
Financial development	FD	0.099	0.995	0.049	−0.120
Gross Domestic Product per capita	PGDP	−0.995 *	1.116	−0.146	−0.116
Urban precipitation	UP	−0.167	0.422	−0.006	−0.203 *** (↑)
Ventilation coefficient	VC	0.082	1.418	−0.021	0.034
Upgrading of industrial structure	UIS	−0.013 ***	−0.009 (↓)	−0.212 ***	−0.134 * (↓)
Research development investment	R&D	−0.065	−0.584	0.385 ***	−0.338 *** (↓)
Road construction	RC	−0.11	0.479	−0.074	−0.024
Topography of urban terrain	UT	0.272 **	0.155 (↓)	0.07	0.001
Government intervention	GI	0.014 *	0.264 *** (↑)	−0.263 **	0.610 *** (↑)

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. (↑) indicates that the regression coefficient was larger than that in 2007, and (↓) indicates that the regression coefficient was smaller than that in 2007.

3.5. Spatial Heterogeneity of Influencing Factors

Taking SO_2 emission reduction governance in Chinese cities in 2018 as an example, we analyzed the spatial multiscale stratification heterogeneity of influencing factors.

Foreign direct investment had a significant effect on SO_2 emissions, showing a "pollution halo" emission reduction effect that decreased from Chinese northeast to southwest (see Figure 6a,b). Domestic enterprises could make use of the advanced technology and management models introduced by foreign capital to improve the total factor productivity of domestic enterprises. The model of low-carbon and green production and operation was able to reduce industrial SO_2 emissions.

The regional innovation and entrepreneurship level significantly increased SO_2 emissions, with its effect being more significant in northern China than in southern China (see Figure 6c,d). This showed that the higher the level of urban innovation and entrepreneurship, the greater the promotion of economic development. In this way, the regional innovation and entrepreneurship level could accelerate the concentration of urban capital, resources, and technology; integrate the industrial and innovation chains of enterprises; also, promote the prosperity of the manufacturing industry. Industry developments cannot be separated from the massive consumption and utilization of resources, which leads to an increase in SO_2 emissions for a short time.

Population intensity, financial development, and urban precipitation significantly reduced SO_2 emissions (See Figure 6e–j). In China, the emission reduction effect of population intensity in southern cities was more significant than that in northern cities; the emission reduction effect of financial development and precipitation in eastern cities was better than that in central and western cities. Population intensity generated a strong agglomeration of the emission reduction effect. Financial development could effectively reduce SO_2 emissions through the regulatory role investment and financing can play in influencing the speed, transformation, and scale of industrial development. The reduction in SO_2 emissions through precipitation was due to a series of liquid-phase chemical reactions that form acidic compounds.

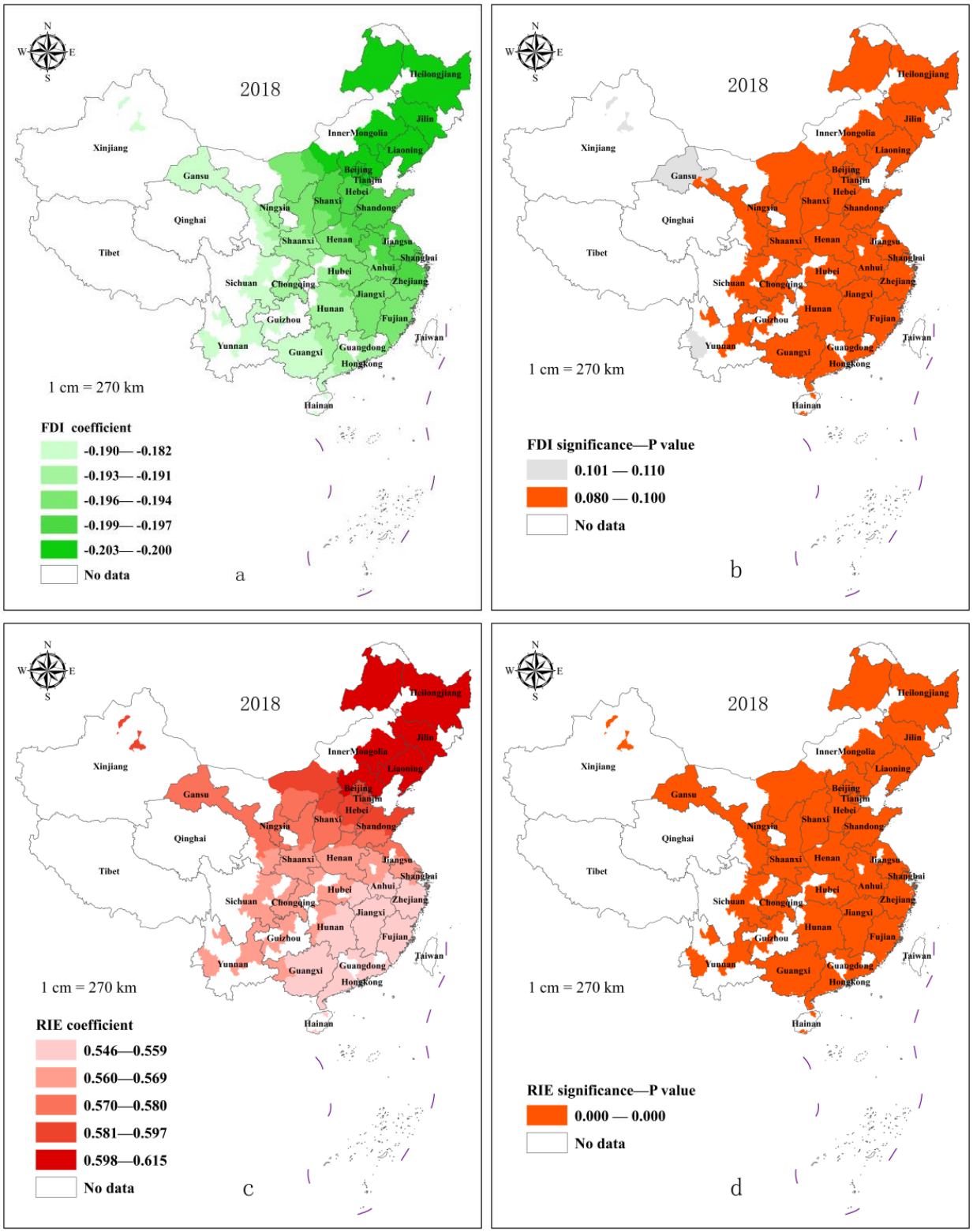


Figure 6. *Cont.*

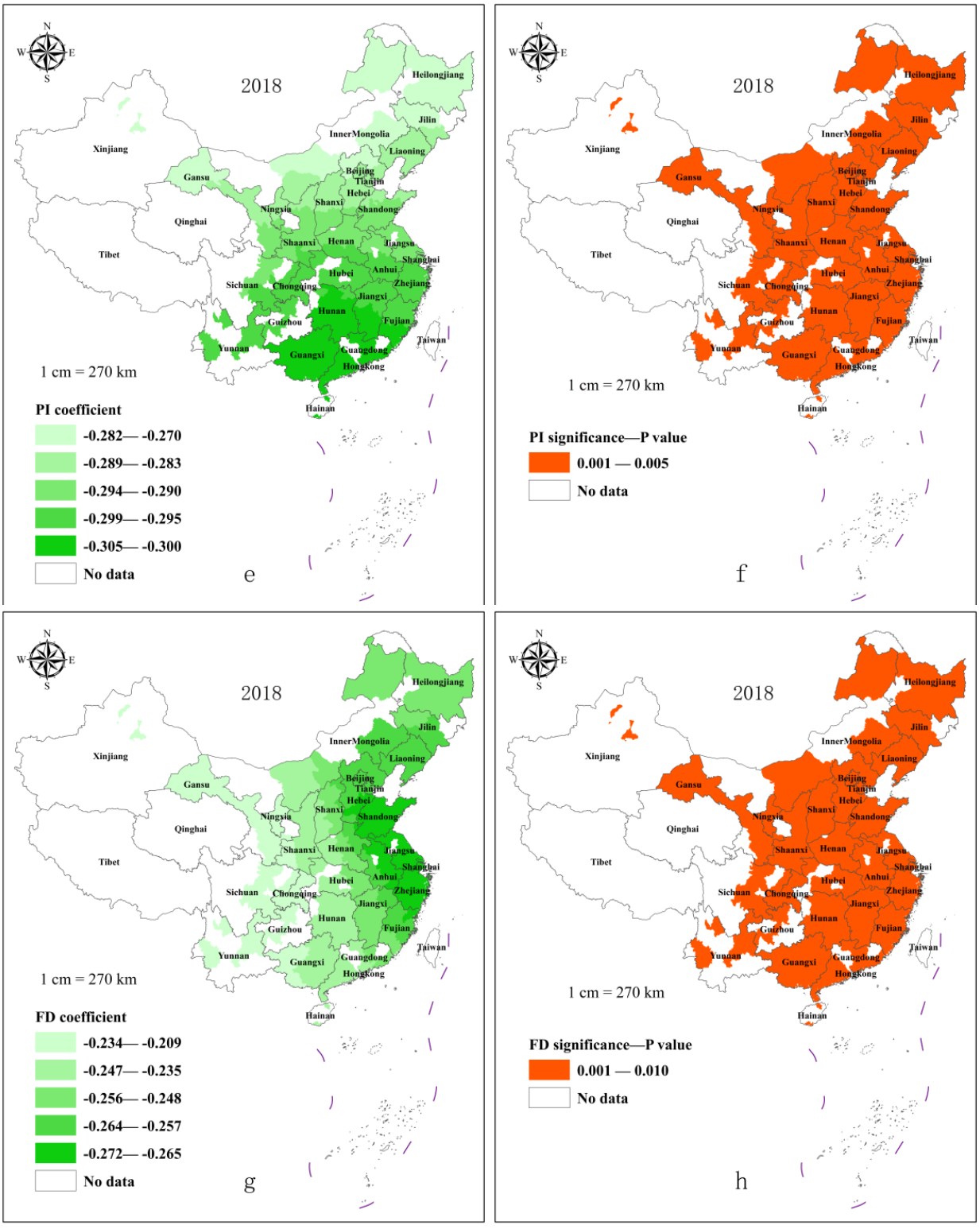


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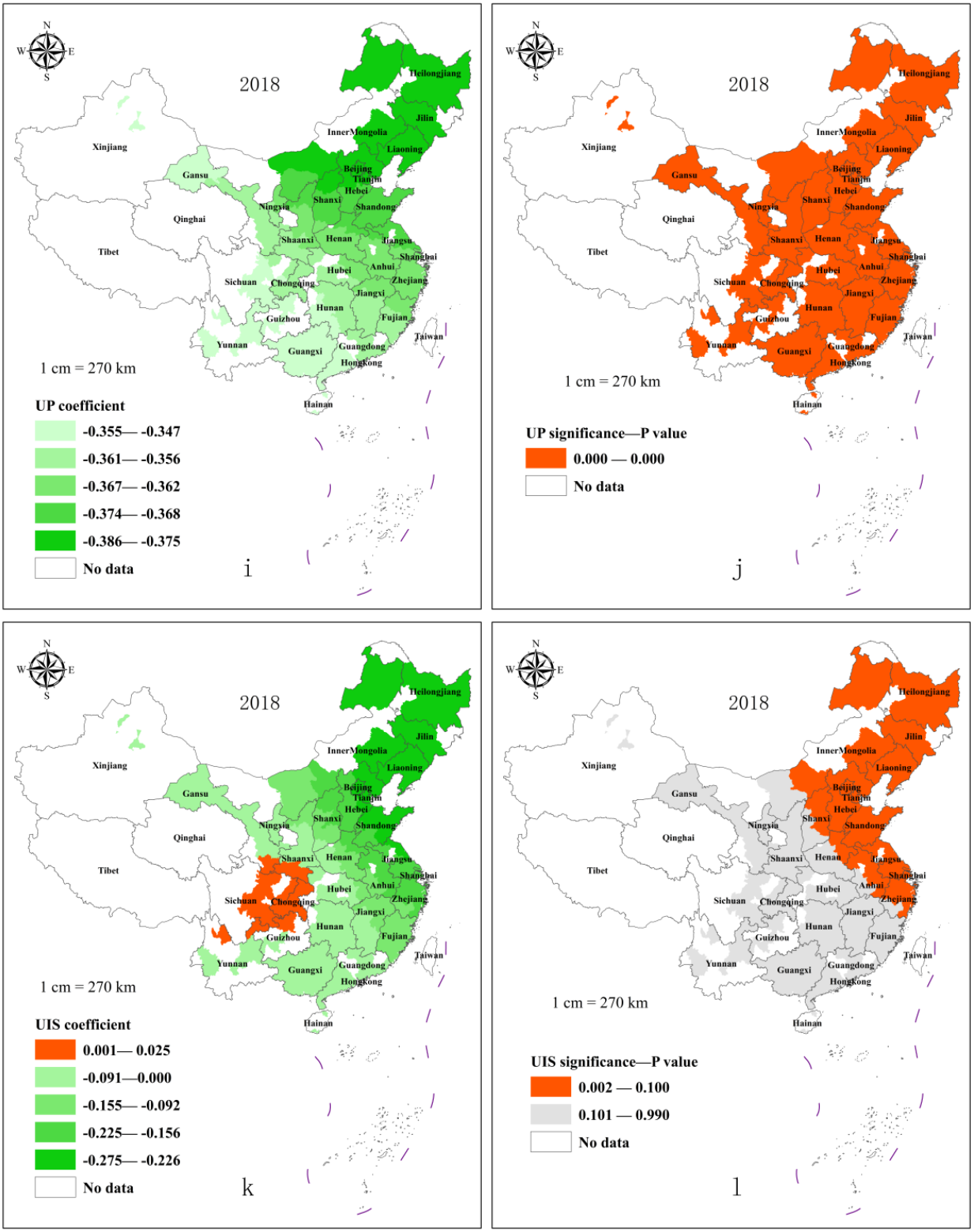


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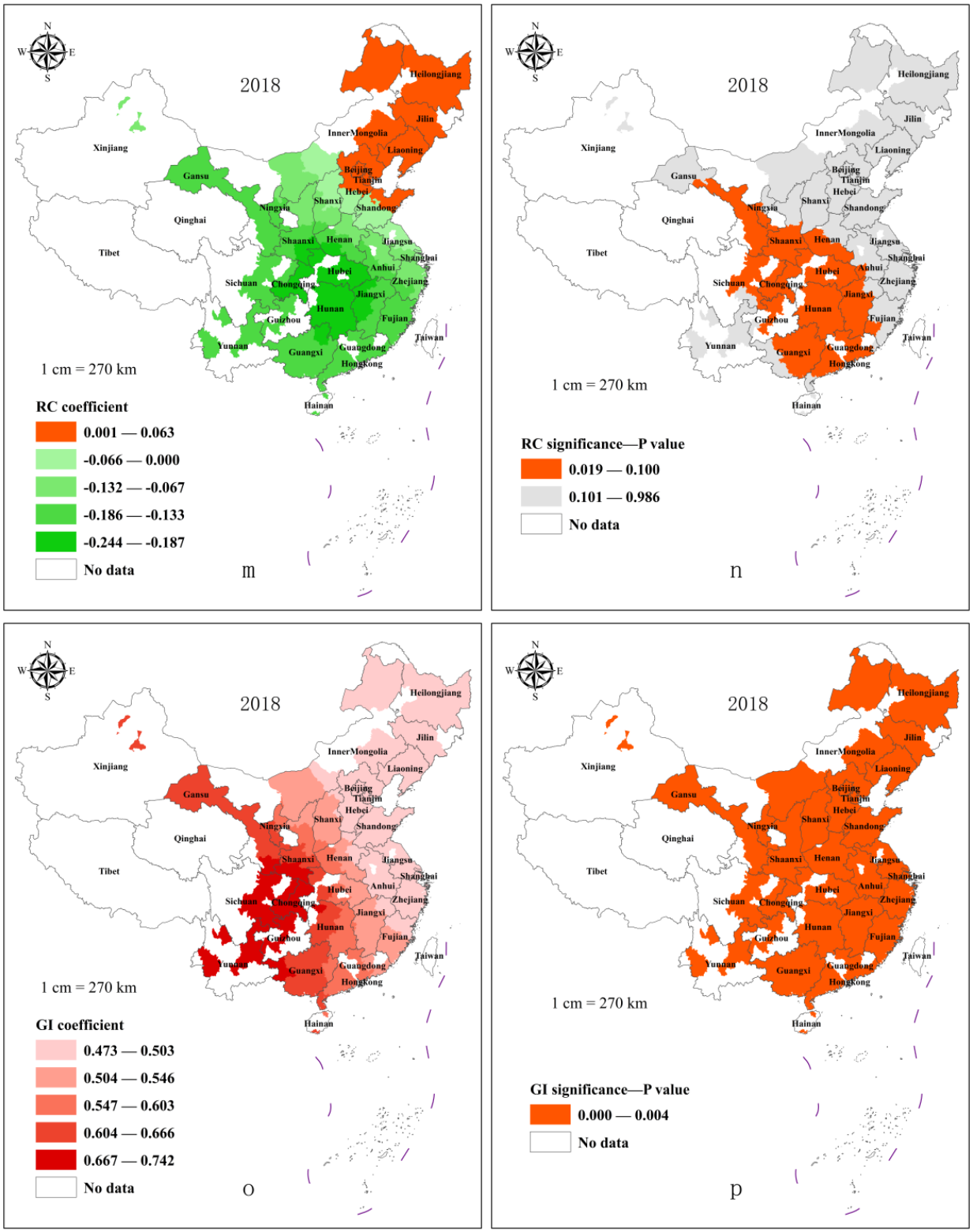


Figure 6. Regression coefficient and significance spatial distribution of influencing factors of SO_2 emissions in 270 cities in 2018. Note: (**a**,**b**), (**c**,**d**), (**e**,**f**), (**g**,**h**), (**i**,**j**), (**k**,**l**), (**m**,**n**), (**o**,**p**) represent the regression coefficient and significance level of FDI, RIE, PI, FD, up, UIS, RC, and GI, respectively.

The upgrading of industrial structures had a significant impact on SO_2 reduction in cities of northeast China, northern China, and eastern China, which accounted for 42.96% of the total sample (Figure 6k,l). The innovative green transformation of industrial

development promoted the revitalization of the old industrial bases in northeast China and the rise of cities in the central region, and reduced the dependence on the "three high"(high pollution, high energy consumption, and high water consumption) industries, which also reduced SO_2 emissions.

Urban road construction showed a significant impact on the increase in SO_2 emissions in the southwest cities, accounting for 37.78% of the total sample (Figure 6m,n). The reason why SO_2 emissions increased is that the large-scale construction of infrastructure directly drives the development of high-carbon emission industries, such as building materials, cement, steel, etc. In addition, road construction also indirectly led to an increase in vehicle consumption and fossil energy.

Government intervention significantly increased SO_2 emissions, which was more obvious in cities of western China than in cities of northeast, northern, and eastern China (Figure 6o,p). Affected by central financial support and transfer payments, the economic development of cities in western China has been quite different from that of cities in eastern China. Large-scale investments, heavy chemical industry projects, infrastructure construction, and government intervention investments in China's western development strategy promoted rapid economic development, but also increased SO_2 emissions.

In addition, we found that the regression results for GDP per capita, the ventilation coefficient, research development investment, and the topography of urban terrain influencing SO_2 emissions did not pass the significance test in the elastic spatial scale.

4. Discussion

4.1. Influencing Factors in Average and Multiscale Spaces

As was mentioned above, the factors influencing Chinese urban SO_2 emissions were significantly differentiated and divergent on the spatial scale in 2018. We captured the main influencing factors of urban SO_2 emissions using the mean values and statistical significance of coefficients. The main influencing factors of urban SO_2 emissions were: the regional innovation and entrepreneurship level, government intervention, urban precipitation; the important factors were: population intensity, financial development, foreign direct investment; the minor factors were: industrial structure upgrading, road construction. Among these factors, the regional innovation and entrepreneurship level and government intervention were the main causes of increases in SO_2 emissions, and the other influencing factors could reduce SO_2 emissions(see Table 5).

Table 5. Regression results of MGWR model.

Variables	English Abbreviation	Mean Value	Standard Deviation	Minimum Value	Median Value	Maximum Value
Constant term	Intercept	0.001	0.006	−0.011	0.000	0.019
Foreign direct investment	FDI	−0.196 *	0.004	−0.203	−0.196	−0.182
Regional innovation and entrepreneurship level	RIE	0.571 ***	0.018	0.546	0.566	0.615
Population intensity	PI	−0.293 ***	0.007	−0.305	−0.295	−0.27
Financial development	FD	−0.250 ***	0.014	−0.272	−0.253	−0.209
Per capita GDP	PGDP	−0.293	0.005	−0.299	−0.295	−0.277
Urban precipitation	UP	−0.365 ***	0.009	−0.386	−0.365	−0.347
Ventilation coefficient	VC	−0.029	0.012	−0.052	−0.031	−0.007
Upgrading of industrial structure	UIS	−0.126	0.095	−0.275	−0.114	0.025
Research development investment	R&D	−0.179	0.007	−0.205	−0.179	−0.166
Road construction level	RC	−0.103	0.089	−0.244	−0.141	0.063
topography of urban terrain	UT	−0.021	0.344	−0.906	−0.079	0.649
Government intervention	GI	0.551 ***	0.083	0.473	0.517	0.742

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

4.2. Heterogeneity of Different Classification Dimensions

Since SO_2 emissions are affected by various factors, such as geographic space, pollution level, resource endowment, and city scale, it was necessary to divide the study samples into different classification dimensions in order to analyze the influencing factors of the SO_2 emissions. The regression results are shown in Table 6.

Table 6. Regression results of MGWR model for geographical classification.

Variable	Northern City	Southern City	Eastern City	Central-Eastern City
Intercept	0.051	−0.161	−0.258 *	0.046
FDI	−0.146	−0.270 *	−0.324	−0.256 *
RIE	0.358 *	0.513 ***	0.400 *	0.626 ***
PI	−0.268	−0.299 **	−0.265	−0.247 **
FD	−0.154	−0.279 **	−0.082	−0.272 ***
PGDP	1.301 *	−0.410	−0.509	−1.046
UP	−0.214 **	−0.013	−0.365 *	−0.200
VC	−0.312	−0.141	−0.105	0.029
UIS	−0.033	−0.084	−0.391	−0.077
R&D	−0.752 **	−0.275	−0.042	−0.110
RC	0.062	−0.118	0.008	−0.318 **
UT	0.073	−0.154	0.022	0.042
GI	0.979 **	0.785 ***	0.606	0.531 ***
R^2	0.447	0.549	0.444	0.482
AICc	350.838	354.544	248.566	496.325
City Number	127	143	82	188

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

According to their geographical orientation, the 270 Chinese cities were divided into northern, southern, eastern, and central–western cities. The factors affecting SO_2 emissions in China's northern cities were government intervention, per capita GDP, the regional innovation and entrepreneurship level, research development investment, and urban precipitation. The factors affecting SO_2 emissions in China's southern cities were government intervention, the regional innovation and entrepreneurship level, population intensity, and financial development. The results of the geographic classification regression were generally consistent with the overall baseline regression, with southern cities showing a more pronounced emission reduction effect than northern cities. We also found that the increase in scientific research investment in northern Chinese cities was conducive to SO_2 emission reduction.

The factors affecting SO_2 emissions in Chinese eastern cities were regional innovation environment and urban precipitation, while the influencing factors affecting SO_2 emissions in Chinese central and western cities were the regional innovation and entrepreneurship level, government intervention, road construction, financial development, population intensity, and foreign investment. The results showed that the means of SO_2 emission reduction in central and western Chinese cities were more diversified than those in Chinese eastern cities. Therefore, under the natural geospatial classification, the main influencing factors affecting SO_2 emission were different.

According to different dimensions of SO_2 emission levels, resource endowment and urban population scales, the influencing factors affecting SO_2 emission were explored. The regression results are shown in Table 7.

The sample cities were divided into high and low SO_2 emissions groups according to their SO_2 emissions mean values. The influencing factors of SO_2 emissions were the regional innovation and entrepreneurship level, population intensity, the upgrading of industrial structures, and urban precipitation, which were consistent with the results of the baseline regression. Cities with high emissions of SO_2 had more obvious emission reduction effects and more potential for a further reduction.

Table 7. Regression results of MGWR model classified by different dimensions.

Variables	Cities with High SO_2 Emissions	Cities with Low SO_2 Emissions	Resource-Based Cities	Non-Resource-Based Cities
Intercept	−0.058	−0.112	0.126	−0.181
FDI	0.135	0.160	0.015	−0.306 **
RIE	0.575 ***	0.424 ***	0.125	0.759 ***
PI	−0.473 **	−0.319 ***	−0.155	−0.407 ***
FD	−0.234	−0.014	0.092	−0.231 **
PGDP	−0.498	0.461	0.551	−1.141 ***
UP	−0.376 **	−0.073 *	−0.169	−0.254 **
VC	−0.108	0.059	0.025	−0.021
UIS	−0.368 **	−0.223 **	−0.062	−0.161 *
R&D	0.127	−0.004	−0.092	−0.268
RC	−0.111	0.000	−0.158	−0.191 **
UT	0.004	−0.109	−0.097	0.044
GI	0.312	0.077	0.593 ***	0.738 ***
R^2	0.389	0.328	0.482	0.602
AICc	277.812	490.61	294.624	379.243
Number of Cities	90	180	109	161

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

According to China's State Council on the Issuance of National Sustainable Development Plan for Resource-based Cities (2013–2020) (Guo Fa (2013) No. 45), all the cities were further divided into resource-based cities and non-resource-based cities. The main influencing factor affecting SO_2 emissions in resource-based cities was government intervention. The reason for this is that local officials focus on short-term urban economic development and highly rely on mineral resource development, resulting in the resource curse effect. The main influencing factors affecting SO_2 emissions in non-resource-based cities were per capita GDP, the regional innovation and entrepreneurship level, government intervention, population intensity, and foreign direct investment. These results verified, once again, the baseline regression. In non-resource-based cities, the methods to reduce SO_2 emissions were more diversified than those in resource-based cities.

5. Conclusions and Suggestions

In this paper, the spatial Moran index, kernel density, hot spot analysis, and standard deviation ellipse were used to analyze the spatio-temporal evolution characteristics of the SO_2 emissions of 270 Chinese cities in 2007 and 2018. Based on the multiscale MGWR model, we quantitatively analyzed the influencing factors of SO_2 emissions in 2018, and could draw the following conclusions:

(1) During the study period, the SO_2 emissions of 270 Chinese cities showed the spatial clustering effect, and the extent and scale of SO_2 pollution declined significantly (by 85.12%). The overall spatial evolution presented a trend of SO_2 emissions moving from "scattered and fragmented high emission" to "contiguous and extensive low emission". The spatial density of SO_2 emissions shifted from south to north in China, and the scope of agglomeration changed from 2007 to 2018.

(2) The results of the standard deviation ellipse of 270 cities in China implied that the spatial distribution direction of SO_2 emissions was "northeast–southwest". The center of the SO_2 emissions standard deviation ellipse shifted to the northeast, from Zhumadian City to Zhoukou City in Henan Province. The results indicated that the cold and hot spots of SO_2 emissions in the studied Chinese cities all increased, showing a polarization trend of "hot spots gathering in the north and cold spots dispersing in the south", while they also suggested that the SO_2 emissions from the cities of China were still in the development period of the differentiative effect.

(3) Regression results based on the MGWR model were more accurate than those estimated by OLS and classic GWR, and choosing different spatial bandwidths had

different effects on the identification of influencing factors. The MGWR model screened out the main influencing factors of SO_2 emissions: the regional innovation and entrepreneurship level, government intervention, and urban precipitation; the important factors: population intensity, financial development, and foreign direct investment; the minor factors: the upgrading of industrial structures and road construction. Among these factors, the regional innovation and entrepreneurship level and government intervention were found to be the main reasons for the increase in SO_2 emissions, while the other influencing factors could contribute to the reduction in SO_2 emissions.

(4) Based on further spatial heterogeneity tests, the regression results were found to be consistent with the baseline regression as a whole. We refined our explanation of the causes of SO_2 emissions in different types of cities, but there was also some spatial heterogeneity and uncertainty with regard to the role of influencing factors. For instance, the increase in scientific research investment in northern cities was found to be conducive to SO_2 emission reduction. Due to the differences in development stages and lifestyles, the impact of per capita GDP on SO_2 emissions in different cities was uncertain. For central–western and non-resource-based cities in China, the means of reducing SO_2 emissions were more diversified.

Urban pollution management is a complex systematic project that is affected by the interaction between social economic activities and the natural ecological environment. The regression results of the MGWR model were more accurate and reliable than OLS and Classic GWR regression. It could carefully explore the urban spatial and heterogeneous impact of the main variables at each time point, clarify the focus on and the direction of SO_2 emission reduction, and provide a scientific basis for decision-makers' rational decision making and space governance. However, there are a number of research questions regarding SO_2 emissions that can be further investigated in the future. For example, the research samples can be further reduced to the county level and enterprises. Factors such as temperature, solar radiation, vegetation coverage, environmental policy, and emission right markets should be considered. The spatially optimized layout of key governance areas will also be the direction of further research.

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