Spatial-temporal characteristics and determinants of PM_{2.5} in the Bohai Rim Urban Agglomeration

Zhen-bo Wang^{a, b}, Chuang-lin Fang^{a, b, *}

^a Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, 11A Datun Road Chaoyang District, Beijing 100101, China

^b Key Laboratory of Regional Sustainable Development Modeling, Chinese Academy of Sciences, Beijing 100101, China

HIGHLIGHTS

- The BRUA was the core area of PM_{2.5} pollution in China.
- PM_{2.5} concentration presenting a U-impulse type daily profile.
- PM_{2.5} concentration showed obvious spatial variation and agglomeration.
- PM_{2.5} concentrations had a negative relationship with GDP per capita.
- PM_{2.5} have positively relationship with urbanization rate and building industry.

GRAPHICAL ABSTRACT

ARTICLE INFO

Article history:

Received 30 September 2015

Received in revised form

25 December 2015

Accepted 27 December 2015

Available online 21 January 2016

Handling Editor: Ralf Ebinghaus

Keywords:

PM_{2.5}

Bohai Rim Urban Agglomeration (BRUA)

Spatial-temporal characteristics

Determinants

Monitoring data

GWR

ABSTRACT

Ambient particulate matter (PM) pollution of China has become a global concern and has great impact on air quality and human health. This paper adopts the PM_{2.5} concentration data obtained from 241 newly located observation points in the Bohai Rim Urban Agglomeration (BRUA), as well as economic, urban and industrial working population data in the study area, revealing the spatio-temporal distribution of PM_{2.5} and its determinants with the help of a spatial data model. The results indicate that: 1) The BRUA was the core area of PM_{2.5} pollution in China in 2014, the average PM_{2.5} concentration of which reached 74 µg/m³, which is 13 µg/m³ higher than the country average (61 µg/m³); 2) The PM_{2.5} concentration distribution had a characteristic of high in winter and autumn but low in spring and summer, presenting a U-shaped monthly profile and a U-impulse type daily profile; 3) The urban PM_{2.5} concentrations showed obvious spatial variation and agglomeration. The highest hot-spot was observed in spring, while the lowest was in summer. High concentration cities were mainly located in southern Hebei and western Shandong, and low concentration cities were in the coastal area around the Bohai Sea and the mountainous areas in northern Hebei. High hot-spot areas demonstrated an M-shaped change, with two cycles of advance and retreat from west to east. 4) The Geographically weighted regression (GWR) model shows that the GDP per capita, urbanization rate and construction of the cities were closely related to PM_{2.5} concentrations in the BRUA.

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1. Introduction

In early 2013, China suffered the most severe haze weather since records began. Rare continuous intense air pollution swept the central and eastern regions (Tian et al. 2014), among which the Bohai Rim region had the highest PM_{2.5} concentrations (Particulate

* Corresponding author. Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, 11A Datun Road Chaoyang District, Beijing 100101, China.

E-mail addresses: wangzb@igsnnr.ac.cn (Z.-b. Wang), fangcl@igsnnr.ac.cn (C.-l. Fang).

matter with aerodynamic diameter $\leq 2.5 \mu\text{m}$), being $680 \mu\text{g}/\text{m}^3$ (Wang et al. 2013). This aroused great concern. The increase in the $\text{PM}_{2.5}$ concentration not only reduces atmospheric visibility (Kan et al. 2012) and impacts negatively on human health (Boldo et al. 2011; Pope and Dockery, 2006), but also impacts climate change by affecting the radiation balance (Wang et al. 2015b). However, the $\text{PM}_{2.5}$ concentration, affected by the intensity of emission sources, topography and climatic factors, is subject to spatial and temporal variability (Cao et al. 2007). Therefore, understanding the variations of $\text{PM}_{2.5}$ concentrations on a national scale is beneficial to us to assess their impact on human health and the environment, and to carry out targeted control measures.

The Bohai Rim Urban Agglomeration (BRUA) is located in the heartland in the western Pacific Rim and Northeast Asia economic circle, including the Beijing municipality, Tianjin municipality, Hebei province, Shandong province and Liaoning province, which comprise the three sub-urban agglomerations of Beijing-Tianjin-Hebei, Shandong Peninsula and central-southern Liaoning. The region has formed a complete urban system. The BRUA is the core area of $\text{PM}_{2.5}$ pollution (Lin et al. 2014). Of the 190 monitoring cities in China in 2014, the top ten highest $\text{PM}_{2.5}$ concentrations were found in the study area. The most seriously polluted city was Xingtai, with an annual average of $131 \mu\text{g}/\text{m}^3$, and several occurrences greater than $500 \mu\text{g}/\text{m}^3$ lasted for more than 30 consecutive periodic s. As 600 million people are exposed to the heavily polluted air with $\text{PM}_{2.5}$ for a long period, the atmospheric pollution control is going to be a major concern in this region. To get a better understanding of the changes in $\text{PM}_{2.5}$ concentration in the Bohai Rim, we should examine the relationship between rapid urbanization and $\text{PM}_{2.5}$ pollution, as well as major social and economic factors related to $\text{PM}_{2.5}$ pollution. All this can help to assess the influence of $\text{PM}_{2.5}$ pollution on human health and the environment in seriously polluted regions and to lay foundations for pollution prevention and control.

In China, research on $\text{PM}_{2.5}$ focused on the urban areas of the Pearl River Delta (Ho et al. 2014), the Yangtze River Delta (Hu et al. 2014), and the Beijing-Tianjin-Hebei Area (BTHA) (Zhao et al. 2013). BTHA is the core area of the BRUA (Wang et al. 2014). In BTHA, most of the studies about $\text{PM}_{2.5}$ have been carried out in Beijing. Most studies have focused on the chemical composition (Ye et al. 2003; Duan et al. 2014), concentrations (Guo et al. 2014), seasonal variations (Han et al. 2010; Liu et al. 2014; Yun et al. 2013), or sources (Zheng et al. 2005; Peng et al. 2013). Zhao et al. (2013) analyzed the characteristics of concentrations and chemical composition of $\text{PM}_{2.5}$ in the BTHA with the data of four urban monitoring sites (Gu et al. 2014). Large-scale research has been based on satellite observation, such as aerosol optical thickness (AOT). AOT data can be used to reveal the spatial heterogeneity characteristics of $\text{PM}_{2.5}$ concentration with the help of linear regression models (Wang and Christopher, 2003), but this data can reflect neither different temporal scales (seasonal, monthly and daily changes) of $\text{PM}_{2.5}$ distribution (Hoff et al. 2009) nor spatial distribution of near-ground $\text{PM}_{2.5}$ (Paciorek and Liu 2009). All these studies were carried out with $\text{PM}_{2.5}$ observations of less than $100 \mu\text{g}/\text{m}^3$, because higher $\text{PM}_{2.5}$ concentrations will lead to biased and inaccurate predictions (Liu et al. 2005), which happens in Beijing. Besides, missing values frequently occur in AOT data, especially when it is cloudy or hazy (Gupta et al. 2006). Monitoring data is typically represented in high dimensionality data sets in which each pollutant is assigned a concentration for each time period of observation, which could well reflect the $\text{PM}_{2.5}$ concentration within the target region (Austin et al. 2013).

With further research on the physical properties of $\text{PM}_{2.5}$, the relationship and mechanism between socioeconomic factors and $\text{PM}_{2.5}$ has aroused great interest from scholars (Paatero et al. 2003).

The main contents included the economic losses due to $\text{PM}_{2.5}$ (Yin et al. 2011), the health assessments of residents (Vera and Cifuentes, 2009), the correlation between a specific industry and the emissions of $\text{PM}_{2.5}$ (Neophytou et al. 2014) and so on. Some other researchers discussed the relationship between $\text{PM}_{2.5}$ and macroscopic socioeconomic factors. Lin et al. (2014) applied remote sensing data to examine the spatio-temporal variation of $\text{PM}_{2.5}$ concentrations and their relationship with geographic and socioeconomic factors from 2001 to 2010 in China. The results show that local economic growth and urban expansion are the two main driving forces impacting $\text{PM}_{2.5}$ concentrations (Lin et al. 2014). Guan et al. used the multi-resolution emission inventory for China and the input–output data of the related years to discuss the socioeconomic drivers of China's primary $\text{PM}_{2.5}$ emissions. Results showed that capital formation and exports are the final demand categories driving emission growth between 1997 and 2010 (Guan et al. 2014). Hu et al. adopted the $\text{PM}_{2.5}$ hourly observed data to discuss the spatial and temporal variability of $\text{PM}_{2.5}$ and PM_{10} over the North China Plain and the Yangtze River Delta in July and August of 2013. Cities within a distance of 250 km have a strong temporal correlation. Meanwhile, $\text{PM}_{2.5}$ was found to be negatively associated with wind speed (Hu et al. 2014). Existing research is more likely to focus on the relationship with a specific industry or a small number of social and economic indicators and $\text{PM}_{2.5}$. However, there are fewer studies on the spatio-temporal variations of the $\text{PM}_{2.5}$ concentration in the seriously polluted area BRUA. Nor is there much research focused on the relationship between $\text{PM}_{2.5}$ pollution and rapid urbanization, as well as the study of the related socioeconomic influencing factors, which is given priority in current research.

Also, to overcome the limitation of linear regression, various methods were applied, such as a two-stage generalized additive model (Liu et al. 2009), support vector regression (Nguyen et al. 2014), GWR (Hu et al. 2013), classical Ordinary Least Square (OLS) and spatial error (Wang et al. 2015a,c,d), and land use regression (Mao et al. 2012), among which GWR embeds the data's spatial location into the regression parameter (Fotheringham et al. 2002), which could well reveal the spatial relationship between $\text{PM}_{2.5}$ concentration and social and economic variables.

The latest National Ambient Air Quality Standard was issued in February 2012. After being implemented in some key regions, the standard will not be implemented nationwide until 2016. Since 1 January 2014, there have been 945 monitoring sites in 190 cities, 241 of which are located in the BRUA, the largest monitoring coverage extent in China. The sites are used to monitor the 24h $\text{PM}_{2.5}$ concentration, which lays a good basis for research on the spatio-temporal characteristics of $\text{PM}_{2.5}$. The authors collected data from 241 monitoring stations in the BRUA in 2014 to do a quantitative analysis and discussed the factors influencing $\text{PM}_{2.5}$. Based on the analysis, some atmospheric contamination abatement measures could be put forward. The industry classification standard adopted in the paper accords to the International Standard Industrial Classification (ISIC) (2008) and the industrial working population data from the China City Statistical Yearbook was used to represent the industrial scale.

2. Materials and methods

2.1. Study area

The BRUA of China is regarded as the study area in this paper. The BRUA covers an area of $518,000 \text{ km}^2$, accounting for 5.4% of the total area of China. It has a population of 250 million, forming 18.40% of the country's total. At the same time, the Gross domestic product (GDP) of the region was 15,450 billion yuan, accounting for 23.90% of the whole country. As one of the three major national-

level metropolitan regions, the BRUA plays an important role in the development of the coastal area of China. In 2014, the Chinese Government agreed that the coordinated development of Beijing-Tianjin-Hebei (BTH) would be a national strategy, which reveals that the BRUA has become a new growth pole.

2.2. Data sources

The PM_{2.5} concentration data is derived from data from the urban air quality real-time publishing platform of the China National Environmental Monitoring Centre. The hourly PM_{2.5} concentration samples are from 241 monitoring sites (Fig. 1) in 54 cities in provincial administrative units including Beijing, Tianjin, Hebei, Shandong and Liaoning in 2014. Among them, there are 165 (68.46%) monitoring sites in urban, 40 (16.60%) in sub-urban and 36 (14.94%) in rural. The Thermo Fisher 1405F monitor was chosen as the main device. The principle is that the sampling air is pumped into the device at a constant flow rate (16.67 L/min), with the aid of a sampling cutter, combined with a filter dynamics measurement system (FDMS) and tapered element oscillating microbalance (TEOM). According to GB3095-2012, requirements for the validity

of air pollutants concentration data, we conducted PM_{2.5} data quality control. First, we excluded the values ≤ 0 in an hour and the missing values of PM_{2.5} concentrations in the raw data; second, in calculating the daily mean, if the missing monitoring data for any day covers more than 4 h, the data for that day is considered invalid, and thus was deleted; third, in calculating the monthly mean, if the monitoring data for that month covers less than 27 days, then the data for that month is invalid, and thus is deleted; fourth, in calculating the annual mean, if the lack of monitoring data of the year covers less than 324 days, then the data for that same year is considered invalid, and was thus deleted; finally, we removed some abnormal values of $>900 \mu\text{g}/\text{m}^3$ in an hour. Data is variable across the monitoring sites. In this study, the monitored 24-hr averaged PM_{2.5} concentrations at all the stations in a city represented the pollution level of the city. On average, 354 valid days were obtained in 2014 for each station we obtained across the country (data is missing or invalid for March 29–31, May 25–26, July 14, September 27–29 and December 27–28 and was removed). On the whole, the percentage of invalid data was 3.02%. According to the definition of GB3095-2012, herein “daily average” means the arithmetic mean of a natural daily 24-h average of concentrations, “monthly average”

Fig. 1. Spatial distribution of the air quality monitoring stations of the BRUA in 2014.

means the arithmetic average of the mean concentrations for each day in a calendar month, “seasonal average” means the arithmetic average of the mean concentrations for each day in a calendar quarter, “annual (yearly) average” means the arithmetic average of the mean concentrations for each day in a calendar year (Ministry of Environmental Protection of the People's Republic of China (2012a,b)); spring refers to March to May, summer covers June to August, autumn refers to September to November, and winter covers January, February and December.

This paper preliminarily selects the affecting variables from three aspects, namely the urban economic development level, urban scale and urban industrial structure. GDP and GDP per capita are used to represent the urban economic development level, urbanization rate represents the urban scale and the size of the urban industrial working population stands for the industrial structures of the city. In 2014, the data including GDP, GDP per capita and urbanization rate is derived from the city government work report in 2015 of each city. The urban industrial working population data is from the City Statistical Yearbook of 2014, among which the 19 industries include persons employed in primary industry, mining, manufacturing, production and distribution of electricity, gas and water, construction, tertiary industry, traffic, transport, storage and post, information transmission, computer services and software, wholesale and retail trades, hotels and catering services, financial intermediation, real estate, leasing and business services, scientific research, technical service and geologic prospecting, management of water conservancy, environment, services to households and other services, education, health, social security and social welfare, culture, sports and entertainment, public management and social organization.

2.3. Methods

2.3.1. Spatial hot-spot analysis method

The spatial autocorrelation model was used to analysing the spatial hot-spot of PM_{2.5} concentrations. Tobler (1970) put forward the First Law of Geography that any object is related to other objects with special consideration of distance, which shows that the more closely located the objects are, the stronger the correlation that exists between them. It is called spatial autocorrelation which can be measured by Moran's I (Moran, 1948; Geary, 1954). When the observation values are similar within a certain distance (d), the Moran's I is positive at a significant level (with p value less than 0.1), otherwise it is negative. If the observation values are arranged randomly, the value of Moran's I is zero. Moran's I can be classified into Global Moran's I (GMI) and Local Moran's I (LMI) (Anselin, 1995). GMI is used to judge the degree of spatial concentration of China's PM_{2.5}, and LMI is used to explore the spatial distribution of the “Hot Spots” and “Cold Spots”. Due to the possible local spatial autocorrelation observations existing in the overall spatial random sample distribution, GMI and LMI are both applied in this paper to analyze the hot-spot features of the PM_{2.5} concentration (Wang et al. 2015a,b,c,d). GMI refers to:

$$I = \frac{n}{S_0} \times \frac{\sum_{i=1}^n \sum_{j=1}^n w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^n (x_i - \bar{x})^2} \quad (1)$$

where n is the total number of the sample, x_i and x_j are respectively the PM_{2.5} in places of i and j . $\bar{x}$ is the average value for a station, w_{ij} is the spatial weight matrix ($n \times n$), it stands for the spatial neighbor relationship of stations i and stations j . w_{ij} would be 1 When stations i and j are adjacent, otherwise, w_{ij} would be 0. and S_0 is the sum of all its elements. LMI is defined as:

$$I_i = n(x_i - \bar{x}) \sum_{j=1, j \neq i}^n w_{ij} (x_j - \bar{x}) \quad (2)$$

$$\text{expected value as : } E(I_i) = -W/(N-1) \quad (3)$$

$$\text{Where } W_i = \sum_j w_{ij} \quad (4)$$

Local Moran's I is the regional components of Moran's I. I_i stands for the influence degree on the whole region spatial autocorrelation from local spatial autocorrelation. It reflects the influence by spatial autocorrelation of various regions to spatial autocorrelation of the region as a whole.

The significance test of Moran's I is measured by Z , Z is the standardized value of I . It can be defined as follows:

$$Z_i = \frac{I - E(I)}{SD(I)} \quad (5)$$

$SD(I)$ is the standard deviation of I .

When I_i and Z_i are both positive at a significant level with p value less than 0.05, it means that the PM_{2.5} concentrations in place i and the units nearby are high. It is termed as a High Concentration Area (HH); by contrast, while I_i and Z_i are negative, it is shown that the PM_{2.5} concentrations in place i and its neighboring units are low, which are called Low Concentration Areas (LL). If I_i is positive and Z_i is negative, it means that the PM_{2.5} concentrations of place i is higher than that of the neighboring units, which are referred to as High Low Concentration Areas (HL). While if I_i is negative and Z_i is positive, the PM_{2.5} concentrations of place i is lower than that of the units nearby, which are termed as Low High Concentration Areas (LH).

2.3.2. The selection methods of PM_{2.5} determinants

- (1) The preliminary selection method of PM_{2.5} affecting variables

The correlation coefficient is applied to analyze the relationship between the PM_{2.5} concentrations of cities in China and urban characteristic variables, so that the affecting factors of PM_{2.5} can be selected. We assume that x_i stands for the annual average of PM_{2.5} concentration in the i -th city, y_i is one of the variables in the i -th city, then their correlation coefficient is shown below:

$$r = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2} \sqrt{\sum_{i=1}^n (y_i - \bar{y})^2}} \quad (6)$$

where n stands for the number of cities, $\bar{x} = \frac{1}{n} \sum_{i=1}^n x_i$ stands for the average value of x_i , and $\bar{y} = \frac{1}{n} \sum_{i=1}^n y_i$ stands for the average value of y_i . The significance of the correlation coefficient could be judged through the T-test, in which the significance level α would be 0.01 and 0.05, respectively.

- (2) The determinants selection method of PM_{2.5}

The GWR model is the result of the improvement from the traditional regression model to the partial regression model, reflecting the effects that the characteristic values of adjacent points have on the characteristic value of a certain point in space (Wang et al. 2010) and the effect would gradually decrease as the distance increased. In the GWR model, PM_{2.5} and variable data samples of the distance weighting of each point are used for local linear regression, and to analyze the spatial heterogeneity of the

relationship with the local trend and the global trend by the distribution of the output parameters. By the method of geographically weighted regression, the regression coefficient (which may partially affect the weight) of each factor at each grid unit in the study area could be obtained, through which the spatial differentiation of PM_{2.5} factors could be analyzed (Hu et al. 2012). The main points are listed below:

Generally, the form of the global least-square regression model is:

$$j = 1, 2, \dots, n; y_i = \beta_0 + \sum_{j=1}^n \beta_j x_{ij} + \varepsilon_i, \quad i = 1, 2, \dots, m; \quad j = 1, 2, \dots, n \quad (7)$$

where x_{ij} represents the j -th observation value at the point of L_i ; y_i represents the explained variable. ε_i stands for random error term; β_0 stands for constant. The GWR model plays an important role in the extension of the formula, which could be used to estimate the parameter at the partial scale. The model could be expressed as:

$$y_i = \beta_0(u_i, v_i) + \sum_{j=1}^n \beta_{ij}(u_i, v_i) x_{ij} + \varepsilon_i, \quad i = 1, 2, \dots, m; \quad j = 1, 2, \dots, n \quad (8)$$

where y_i represents the observation value of explained variable at the point of L_i ; x_{ij} represents the j -th observation value of the explanatory variable at the point L_i ; (u_i, v_i) stands for the space coordinates of L_i ; $\beta_{ij}(u_i, v_i)$ stands for a value of continuous function $\beta(u_i, v_i)$ at the position L_i .

$$y_i = \beta_0(u_i, v_i) + \beta_1(u_i, v_i) x_{1j} + \beta_2(u_i, v_i) x_{2j} + \dots + \beta_m(u_i, v_i) x_{mj} \quad (9)$$

where x_{mj} is the observation value of the j -th influencing factors at the position of L_m ; $\beta_m(u_i, v_i)$ is the geographic weighting of the PM_{2.5} influencing factors.

On the basis of the First Law of Geography, the observation data at the positions nearby have a greater effect on the estimation of $\beta_m(u_i, v_i)$ than those at distant positions. Hence in the GWR model, the weightings of observation data do not remain unchanged any more during the regression process. How to weight the data is determined by the distance between the study point and the position L_i , that is:

$$\beta(\hat{u}_i, v_i) = (X^T W(u_i, v_i) X^T W(u_i, v_i) Y) \quad (10)$$

where

$$X = \begin{bmatrix} 1 & X_{11} & \dots & X_{1,n} \\ 1 & X_{21} & \dots & X_{2,n} \\ \dots & \dots & \dots & \dots \\ 1 & X_{m1} & \dots & X_{m,n} \end{bmatrix}, \quad Y = \begin{bmatrix} y_1 \\ y_2 \\ \dots \\ y_n \end{bmatrix} \quad (11)$$

$$W_{j(u_i, v_i)} = \begin{bmatrix} W_1(u_1, v_1) & 0 & \dots & 0 \\ 0 & W_2(u_2, v_2) & \dots & 0 \\ \dots & \dots & \dots & \dots \\ 0 & 0 & \dots & W_n(u_m, v_m) \end{bmatrix}, \quad (12)$$

$$\beta = \begin{bmatrix} \beta_0(u_1, v_1) & \beta_1(u_1, v_1) & \dots & \beta_n(u_1, v_1) \\ \beta_0(u_2, v_2) & \beta_1(u_2, v_2) & \dots & \beta_n(u_2, v_2) \\ \dots & \dots & \dots & \dots \\ \beta_0(u_m, v_m) & \beta_1(u_m, v_m) & \dots & \beta_n(u_m, v_m) \end{bmatrix}$$

where $\hat{\beta}$ stands for the estimated value of β ; m stands for the number of independent variables (the number of PM_{2.5}-influencing factors); n is the sample number at space; $W_{j(u_i, v_i)}$ represents the weight matrix of independent variable j at the point of L_i .

3. Result analysis

3.1. The PM_{2.5} concentrations have a W-shaped pattern of “high in autumn and winter but low in spring and summer” in the major cities of China

The annual PM_{2.5} concentration was 74 $\mu\text{g}/\text{m}^3$ for the 54 observed cities in the BRUA in 2014, which exceeded the average level of the whole country (61 $\mu\text{g}/\text{m}^3$). This region had the top 10 cities with the highest PM_{2.5} concentrations in China, including Xingtai, Baoding, Shijiazhuang, Handan, Hengshui and Langfang in Hebei, as well as Dezhou, Heze and Liaocheng in Shandong. Among the cities, the annual average of PM_{2.5} concentrations of the top seven cities was over 100 $\mu\text{g}/\text{m}^3$. According to *Ambient Air Quality Standards* (AAQS; GB 3096-2012), only Zhangjiakou (34 $\mu\text{g}/\text{m}^3$) just reached the national annual air quality standard, and it outclass the *24h Air Quality Standards of WHO* (25 $\mu\text{g}/\text{m}^3$). Meanwhile, the PM_{2.5} concentrations of 24 cities did not reach the national 24 h air quality standard (75 $\mu\text{g}/\text{m}^3$).

3.1.1. PM_{2.5} concentrations are low in spring and summer but high in winter and autumn

The PM_{2.5} concentration in the BRUA had a distinct seasonal change. Among the seasons, the highest value appeared in winter, with an annual average of 119 $\mu\text{g}/\text{m}^3$. The highest observed data appeared in Shijiazhuang (242 $\mu\text{g}/\text{m}^3$), while the lowest was in Yingkou (65 $\mu\text{g}/\text{m}^3$), which was directly related to emissions due to coal combustion for winter heating in northern China. Autumn took second place, with the average value of 65 $\mu\text{g}/\text{m}^3$, during which the highest value was in Baoding (125 $\mu\text{g}/\text{m}^3$) and the lowest was in Zhangjiakou (23 $\mu\text{g}/\text{m}^3$). And then, the average concentration in spring was 61 $\mu\text{g}/\text{m}^3$, with the maximum in Xingtai (106 $\mu\text{g}/\text{m}^3$) and the minimum in Zhangjiakou (27 $\mu\text{g}/\text{m}^3$). The minimum was observed in summer, with the average being 51 $\mu\text{g}/\text{m}^3$. During this season, the maximum value was found in Shijiazhuang (94 $\mu\text{g}/\text{m}^3$) and the minimum in Zhangjiakou (20 $\mu\text{g}/\text{m}^3$).

3.1.2. Monthly average PM_{2.5} concentrations show a U-shaped change

From a monthly point of view, the PM_{2.5} concentration of the BRUA from January to December in 2014 illustrated a U-shaped fluctuation (the sub-panel in Fig. 2). From January (118 $\mu\text{g}/\text{m}^3$) to June (55 $\mu\text{g}/\text{m}^3$), the data showed a decreasing trend; in June and July (60 $\mu\text{g}/\text{m}^3$), the northern parts of China would experience the rainy season accompanying the air of higher humidity. Therefore, PM_{2.5} would absorb moisture making the observation data higher in value, and the data slightly increased; With the rainy season gone, there was a slight decrease in August (52 $\mu\text{g}/\text{m}^3$) and September (48 $\mu\text{g}/\text{m}^3$) but after that, the concentration showed an increasing trend. In 2014, the concentration level of the BRUA in January, February, March, November and December was over 75 $\mu\text{g}/\text{m}^3$, while that of the other months was 48–75 $\mu\text{g}/\text{m}^3$. The PM_{2.5} concentration reached its peak in January, and the maximum and minimum values were observed in Xingtai (256 $\mu\text{g}/\text{m}^3$) and Yingkou (41 $\mu\text{g}/\text{m}^3$), respectively. The monthly value of September was the lowest in 2014 (48 $\mu\text{g}/\text{m}^3$), the maximum and minimum appeared in Hengshui (87 $\mu\text{g}/\text{m}^3$) and Zhangjiakou (21 $\mu\text{g}/\text{m}^3$) respectively (Fig. 2).

Fig. 2. The monthly change in $PM_{2.5}$ concentration in the BRUA in 2014.

3.1.3. Daily average $PM_{2.5}$ concentrations present a U-impulse type profile

The $PM_{2.5}$ daily concentration overall presented a U-impulse-type with a characteristic of high in spring and winter and low in summer and autumn throughout the year (the sub-panel in Fig. 3). The daily maximum value was on 16 January ($216 \mu\text{g}/\text{m}^3$), while the minimum was on 3 September ($22 \mu\text{g}/\text{m}^3$). From the perspective of the daily average value, the concentration curve of the BRUA had an obvious periodic fluctuation in 2014. The wave length is longer in summer and autumn, but shorter in spring and winter, with a period averaging five days (Fig. 3). This is highly consistent with the cold air activity cycle lasting for about 5 days in north China. According to weekly data of 2014, we calculated the frequency of weekday/weekend when $PM_{2.5}$ concentration was more than $75 \mu\text{g}/\text{m}^3$. It could be seen that the $PM_{2.5}$ of Wednesday, Thursday, Friday and Saturday were higher; and Sunday, Monday, Tuesday were lower.

3.1.4. The air quality of the BRUA is obviously below the national average and there are more high-level polluted cities in winter and autumn, while fewer in spring and summer

According to 24-hr pollution levels in China defined in the technical requirements based on the Ambient Air Quality Index

(AAQI) (Trial) (HJ633-2012), the $PM_{2.5}$ concentrations were divided into six grades, namely excellent ($0-35 \mu\text{g}/\text{m}^3$), good ($35-75 \mu\text{g}/\text{m}^3$), slightly polluted ($75-115 \mu\text{g}/\text{m}^3$), moderately polluted ($115-150 \mu\text{g}/\text{m}^3$), heavily polluted ($150-250 \mu\text{g}/\text{m}^3$), and seriously polluted ($250-500 \mu\text{g}/\text{m}^3$). We calculated the daily $PM_{2.5}$ concentrations in all of the 54 cities, and obtained the number of days for each grade in each city. Results showed that in 2014, the number of days where the standard of good air quality was reached was 224, and 30 cities reached this level. Overall, seen from the average $PM_{2.5}$ concentrations in 2014, there were more cities and more days with good air quality in summer, followed by autumn and spring, with the least in winter. In summer, 76.41% of cities, or 70 days reached the standard, followed by autumn (64.60%, or 56 days) and spring (64.24%, or 56 days), winter (47.62%, or 42 days). Based on the monthly data, 70% reached the standard from May to September, with August at the highest level (83.13%), followed by April and October at 60%–70%, March and December at 50%–60%, February and November at 40%–50%; the lowest was January at 37.63%. There were more pollution days in winter, fewer in summer, autumn and spring. January, February, March, November and December witnessed the largest proportion of pollution days (more than 40%), with the first month of the year at 62.37%. Heavily and seriously polluted air quality was found in winter, with the latter

Fig. 3. The daily variation in $PM_{2.5}$ of the BRUA in 2014.

occurring in January and February (Fig. 4).

3.2. Spatial differences in $PM_{2.5}$ concentrations in the BRUA

3.2.1. Analysis of annual average spatial distribution shows that $PM_{2.5}$ concentrations present a decreasing trend from the inland (southwest) towards the coastal area (northeast)

Kriging interpolation based on the semi-variogram theory of variable values within a limited region is an optimal method via unbiased estimation, which can clearly explain the spatial distribution of $PM_{2.5}$ concentrations (Wang et al. 2015a,b,c). The BRUA, one of the major $PM_{2.5}$ polluted regions, had an annual average of $74 \mu\text{g}/\text{m}^3$, much higher than the national level ($61 \mu\text{g}/\text{m}^3$). $PM_{2.5}$ pollution in this region presented a decreasing trend from the inland (southwest) towards the coastal area (northeast), namely, Beijing-Tianjin-Hebei and western Shandong were seriously polluted, with central-western Hebei as the core area (Fig. 5a).

The $PM_{2.5}$ annual standard of China is $35 \mu\text{g}/\text{m}^3$. We take the national average ($35 \mu\text{g}/\text{m}^3$) as a daily standard. If the value is $> 35 \mu\text{g}/\text{m}^3$, we say it is 'over-standard'. There were 13 cities (24.07%) with an over-standard rate of $>90\%$ (319 days) in southern Hebei and western Shandong; 23 cities (42.59%) with an over-standard rate of 70%–90% (248–318 days) in central Hebei, central Shandong, Beijing and Tianjin; 15 cities (27.78%) with an over-standard rate of 50%–70% (177–247 days) in northern Hebei, the Shandong Peninsula and the East Liaoning Peninsula. Only three cities had an over-standard rate $<50\%$ (112 days), namely Zhangjiakou (a mountain city), and the coastal cities of Weihai and Yingkou (Fig. 5b).

The $PM_{2.5}$ daily standard of China is $75 \mu\text{g}/\text{m}^3$. We take the average value ($75 \mu\text{g}/\text{m}^3$) as a daily standard. If the value is $> 75 \mu\text{g}/\text{m}^3$, we say it is over-standard. There were 19 cities (35.19%) with an over-standard rate of $>50\%$ (177 days) in southern Hebei and western Shandong; 23 cities (42.59%) with an over-standard rate of 20%–50% (74–176 days) in Beijing, Tianjin, central-northern Hebei, Shandong and central-western Liaoning; 12 cities ($<20\%$) with an over-standard rate $<20\%$ (73 days) in coastal and mountainous areas, of which, Zhangjiakou and Yingkou saw less than 30 days (Fig. 5b). In coastal region, the wind speed is high. But generally its scope of influence only reach 20–50 km inland. In inland regions, $PM_{2.5}$ formation are mainly influenced by terrain and inland wind speed.

3.2.2. Analysis of seasonal average spatial differentiation shows that the heavily polluted cities in winter are concentrated in southern Hebei

According to statistical data from different cities and seasons on the daily rate, the extent of over-standard levels presented a

distribution of "greater in winter, smaller in summer and average in spring and autumn" in the BRUA. Winter (88 days) witnessed an over-standard rate of 52.38% (46 days), with Xingtai, Baoding and Shijiazhuang at $>80\%$ (72 days). Heavily polluted cities (27) with a rate of $>50\%$ were widely distributed in Beijing, Tianjin, Hebei and western Shandong. There were 20 cities (42.59%) with an over-standard rate of 30%–50% (27–43 days) concentrated in the Shandong and East Liaoning peninsulas. Another 8 cities had an over-standard rate of $<30\%$ (73 days), which were mainly found in coastal areas (Fig. 6d). Spring (87 days, Fig. 6a) and autumn (88 days, Fig. 6c) had average over standard rates of 35.75% (31 days) and 35.40% (31 days), with a smaller heavily polluted extent compared with winter. The pollution extent shifted southward because of the frequent occurrence of sandstorms in northern China in spring. 75% of sandstorms occur in March and April of Spring, which mainly cause PM_{10} ; sandstorms rarely happens in winter, summer or autumn, yet occasionally there would be short period of local sand blowing and floating dust. In spring and autumn, cities with an over-standard rate of 50% (44 days) were mainly found in Tianjin, southern Hebei and western Shandong; cities with an over-standard rate of 20%–25% (18–43 days) were distributed in Beijing, Shandong Peninsula, East Liaoning Peninsula, and Tianjin, cities with an over-standard rate of $<20\%$ (17 days) were mainly in coastal areas of the BRUA. Summer (91 days) saw an average over-standard rate of 23.59% (22 days), with Shijiazhuang, Handan and Laiwu at 50% (46 days). There were 18 cities with an average over-standard rate of $>30\%$ (28 days) concentrated in Beijing, Tianjin, southern Hebei and western Shandong. Another 33 cities (over-standard rate $<30\%$) were distributed in coastal peninsular areas (Fig. 6b). On the whole, the number of over-standard days in the BRUA was 10 days, 10 days, 11 days and 7 days more than the national level in spring, summer, autumn and winter, respectively.

3.2.3. In terms of average monthly change, there are three cycles of pollutant dissemination. January and February are the months with highest and widest distribution of $PM_{2.5}$ concentrations

According to monthly data, the highest $PM_{2.5}$ concentration rate occurred in January, with the largest extent. The monthly over-standard rate was 62.37% (19 days) and that of 70.37% of the cities (38 cities) was beyond 50% (16 days), covering the BRUA apart from coastal and northern mountainous areas (Fig. 7a). In addition, the pollution extent of February (Fig. 7b), March (Fig. 7c), November (Fig. 7k) and December (Fig. 7l) ranked behind that of January, with the over-standard rate between 40% and 60% (12–16 days). The area with an over-standard rate of $>50\%$ in February included the eastern part of the BRUA. From March to June, the extent constantly shrank to the southeastern direction. In June, the

Fig. 4. The temporal distribution of cities at different pollution levels in the BRUA in 2014.

Fig. 5. Spatial distribution of $PM_{2.5}$ concentrations in the major cities of the BRUA in 2014.

over-standard rate was 21.6% (6 days) and the first trough value appeared in this period. The over-standard rate in July was 28.89% (9 days), and during this period of time, the over-standard area beyond 50% in the Beijing-Tianjin-Hebei region obviously increased (Fig. 7g). The over-standard rate decreased in August (20.37%, 6 days) and reached the bottom level in September (16.87%, 5 days) (Fig. 7i). After that, the value presented another constant increase from October (Fig. 7j) to December, with a rate of 35.90%, 52.11% and 42.49% respectively, whereas the rate in December was lower than that of November and the seriously polluted extent shifted from Beijing to the southern part of the whole region, which was directly related to the traffic limit in Beijing, Tianjin, Hebei, Shanxi, Inner Mongolia, and Shandong during the APEC Summit in November, as well as the shutdown of major polluters such as the petrochemical industry. The results were consistent with those of Liu et al. (2015), namely, collaborative regional policies and compensation systems for mitigating pollution played a significant role.

3.3. Spatial distribution of $PM_{2.5}$ concentrations in the BRUA

Moran's I (Moran 1948) is a weighted correlation coefficient used to detect departures from spatial randomness. Moran's I is used to determine whether neighboring areas are more similar than would be expected under the null hypothesis. Moran's index ranges from 1 to -1 ; if the locations are not related, the value is expected to be close to 0; when I is a negative value, it generally denotes a negative autocorrelation; when I is a positive value, it indicates a positive autocorrelation. Spatial autocorrelation mainly depends on the z-scores. the z-scores are measures of statistical significance which tell you whether or not to reject the null hypothesis, feature by feature. A high z-score for $PM_{2.5}$ indicates a spatial clustering of high values. A low negative z-score indicates a spatial clustering of low values. The higher (or lower) the z-score, the more intense the clustering. A z-score near zero indicates no apparent spatial clustering. In general, Z is significant when it is greater than 1.96 and it is extremely significant when it is greater than 2.58.

Gi_Bin was used to identify statistically significant Hot Spots and Cold Spots. The Gi_Bin field identifies statistically significant hot and cold spots regardless of whether the FDR correction is applied or not. Features in the ± 3 bins reflect statistical significance with a 99 percent confidence level; features in the ± 2 bins reflect a 95 percent confidence level; features in the ± 1 bins reflect a 90 percent confidence level; and the clustering for features in bin 0 is

not statistically significant. The larger the number of Hot Spots with confidence level $>90\%$, the greater the extent of cities with high $PM_{2.5}$ concentrations.

The Moran's I in 2014 was greater than 0.5 in all the months except May. The monthly value of Moran I was 0.68, close to 1, indicating that $PM_{2.5}$ concentrations had a spatial autocorrelation in this region. In terms of Z (I), its index was 16.72 throughout the year, suggesting that there was a positive autocorrelation of High–High or Low–Low Spots with $PM_{2.5}$ concentrations within the urban agglomeration.

3.3.1. In terms of annual or seasonal distributions, Hot Spots were mainly located in Beijing, Tianjin, southern Hebei and northwestern Shandong

According to Z (I), its index was 20.06, 9.03, 19.49 and 18.29 in spring, summer, autumn and winter respectively (Fig. 8), with spring being the highest, suggesting a strong hot-spot in spring (Fig. 8a), while the weakest hot-spot in summer (Fig. 8b). The number of Hot Spots with confidence level $>90\%$ showed the extent of the areas affected by $PM_{2.5}$ concentrations in this region. Fig. 2 shows that there were 48 monitoring sites with confidence level $>90\%$ in autumn, of which 75.86% exceeded the 99% confidence level, suggesting that the pollutants in this season were highly concentrated in Tianjin and southern Hebei (Fig. 8c). There were 38 and 34 monitoring sites with confidence level $>90\%$ in spring and winter respectively, with 60% of sites with $>99\%$ confidence level, indicating a similar spatial distribution. In contrast, 32 sites had 90% confidence in summer, but those with a 99% level accounted for 6.25% in that season, suggesting a weaker hot-spot. According to annual and seasonal statistics, $PM_{2.5}$ polluted cities were mainly found in Beijing, Tianjin, southern Hebei and northwest Shandong, while cities with excellent and good air quality were mainly located in the Shandong Peninsula, East Liaoning Peninsula and northern Hebei.

3.3.2. Analysis of monthly variations indicates that $PM_{2.5}$ concentrations present an M-shaped cycle with two advances and two retreats from west to east

In terms of monthly variations, $PM_{2.5}$ concentrations presented a distinct autocorrelation in all the months except May. Data from the monitoring sites with confidence level $>95\%$ could reflect spatial variations of $PM_{2.5}$ concentrations (Table 1). Results showed that higher $PM_{2.5}$ concentrations had the largest extent in March and July, whereas the smallest extent was found in May and September, namely an M-shaped cycle with two advances and two

Fig. 6. Seasonal changes of $PM_{2.5}$ in the BRUA in 2014.

retreats from west to east was observed from November to May and May to October (Fig. 9). The reason lies in the fact that during the annual heating period of November, December, January, February and March, there produces a large-scale emission of $PM_{2.5}$ by which the polluted area extends to the largest scope in March. By the end of heating in April, $PM_{2.5}$ concentrations decrease rapidly. The concentrations of $PM_{2.5}$ is relatively low in September as a

whole. But compared to the coastal and mountainous areas, those of plain areas are obviously higher and in even distributions, thus featured by massive spatial hot-spot. The H–H Spots areas expanded from mountainous areas in southern Hebei to western Shandong, Beijing and Tianjin from November to March, reaching the largest polluted extent with 64 monitoring sites. Then the extent retreated westward, reaching the smallest extent in May,

Fig. 7. Spatial distribution of monthly $PM_{2.5}$ concentrations in the BRUA in 2014.

Fig. 8. Spatial agglomeration of seasonal PM_{2.5} concentrations in the BRUA in 2014.

Table 1

Spatial autocorrelation index of PM_{2.5} concentrations in the BRUA.

Month/Season	Moran I	Z(I)	Hot spot			
			T	C ₁ %	C ₂ %	C ₃ %
Jan.	0.84	20.38	48	77.08	2.08	20.83
Feb.	0.78	19.06	43	76.74	13.95	9.3
Mar.	0.69	16.74	64	34.38	53.13	12.5
Apr.	0.53	12.76	43	9.3	46.51	44.19
May	0.06	2.51	3	66.67	33.33	0.00
Jun.	0.64	15.49	27	25.93	77.78	29.63
Jul.	0.75	18.23	60	90.00	5.00	5.00
Aug.	0.85	20.5	47	65.96	12.77	21.28
Sept.	0.81	19.64	53	37.74	39.62	22.64
Oct.	0.82	19.94	31	70.97	6.45	22.58
Nov.	0.69	16.76	41	19.51	34.15	46.34
Dec.	0.72	17.34	38	55.26	47.37	21.05
Spring	0.83	20.06	38	60.53	18.42	21.05
Summer	0.36	9.03	32	6.25	56.25	37.50
Autumn	0.81	19.49	48	75.00	10.42	14.58
Winter	0.75	18.29	34	61.76	2.94	35.29
Annual	0.82	16.72	29	75.86	0.00	24.14

T: Total number of Hot Spots; C₁: The proportion of Hot Spot-99% confidence level; C₂: The proportion of Hot Spot-95% confidence level; C₃: The proportion of Hot Spot-90% confidence level.

only found in cities on the south tip of Hebei. From May to July, the

Fig. 9. Monthly variations of Hot Spots of PM_{2.5} concentrations in the BRUA in 2014.

Fig. 10. Spatial hot-spot of monthly $PM_{2.5}$ concentrations in the BRUA in 2014.

polluted extent expanded towards western Shandong, Beijing and Tianjin, with 60 monitoring sites involved. After that, the extent

retreated southwestward, with the smallest number (31 sites) in October. The L-L Spots areas were mainly located in the Shandong

Peninsula, East Liaoning Peninsula and northern Hebei, which showed an increase or a decrease in succession with the H–H Spots areas (Fig. 10). Based on the average monthly wind speed data (1980–2015) of the study area from the national monitoring sites, the monthly wind speed can be seen in decline from May to August and then raise back. Actually it's one of the reasons for PM_{2.5} to increase at such a fast rate in June.

3.4. The relationship between PM_{2.5} concentrations and industry variables

The cause of PM_{2.5} generation has been a hot topic in academia. Energy consumption is regarded as the source of PM_{2.5}. Urban sprawl, economic development and industrial progress are the final goal of energy consumption. Based on this, we selected 23 indicators to examine the correlation with PM_{2.5} for each city, and then determined which indicators were the main factors influencing urban PM_{2.5} pollution.

3.4.1. Selection of factors influencing urban PM_{2.5} concentrations based on relevant coefficients

We made a relevant analysis of PM_{2.5} concentrations with the 23 economic and social variables in this region. The factors passing the test of $\alpha = 0.01$ included Permanent Resident Population, Per capita GDP, Urbanization Rate, Production and Distribution of Electricity, Gas and Water, Building, Education, Public Management and Social Organization (Table 2). Results showed that the above seven variables are closely related with PM_{2.5} concentrations in the BRUA.

3.4.2. Analysis of factors influencing PM_{2.5} concentrations based on GWR

The selected 7 indicators were checked by a multiple linear test with the help of SPSS22.0. According to the rule, data has no

multiple linearity when Variance Inflation Factor is less than 10 and approaches 1. It is shown that Per capita GDP, Urbanization Rate and Building have no multiple linearity (Table 3). Thus we took the three factors as the variables for GWR analysis.

Analysis of the three factors based on GWR showed that R^2 is 0.839861, suggesting that the GWR model could well explain the correlation between PM_{2.5} concentrations and selected variables (Fig. 11).

4. Conclusions and policy implications

- (1) The BRUA was one of the core regions of PM_{2.5} pollution in China, and the PM_{2.5} concentrations showed an obvious temporal distribution. The annual average PM_{2.5} concentration in 53 monitored cities in the BRUA in 2014 was 73.80 $\mu\text{g}/\text{m}^3$, which was far beyond the national average level (60.82 $\mu\text{g}/\text{m}^3$). In terms of seasonal variation, the PM_{2.5} concentration had the characteristic of low in spring and summer but high in winter and autumn. Seen from the perspective of monthly change, the curve of the PM_{2.5} concentration was W-shaped. From January to May, the concentration declined, followed by a slight increase in June and July. Then, in August and September, the data slightly decreased and showed an upward trend again from October to December. Analysis of daily change indicated that PM_{2.5} concentration of the BRUA had an apparent a U-impulse type variation, with the peak value appearing on 16 January (203 $\mu\text{g}/\text{m}^3$) and the minimum value on 3 September (24 $\mu\text{g}/\text{m}^3$).
- (2) The PM_{2.5} concentration in the BRUA also had obvious spatial distribution. Annual average spatial distribution showed that PM_{2.5} concentrations had a decreasing trend from the inland (southwest) towards the coastal area (northeast), with

Table 2
Significance and correlation coefficients of PM_{2.5} concentrations in the BRUA.

Variables	R	p	Variables	r	p
Permanent Resident Population	0.525	0.000***	Hotels and Catering Services	0.088	0.53
GDP	0.177	0.206	Financial Intermediation	0.16	0.251
Per capita GDP	−0.359	0.008***	Real Estate	0.066	0.64
Urbanization Rate	−0.237	0.087**	Leasing and Business Services	0.069	0.625
Persons Employed in Primary Industry	−0.236	0.088*	Scientific Research, Technical Service and Geologic Prospecting	0.099	0.481
Mining	0.226	0.104	Management of Water Conservancy, Environment	0.171	0.221
Manufacturing	0.127	0.365	Services to Households and Other Services	0.1	0.475
Production and Distribution of Electricity, Gas and Water	0.358	0.009***	Education	0.39	0.004***
Construction	0.383	0.005***	Health, Social Security and Social Welfare	0.27	0.051*
Traffic, Transport, Storage and Post	0.101	0.474	Culture, Sports and Entertainment	0.098	0.483
Information Transmission, Computer Services and Software	0.074	0.599	Public Management and Social Organization	0.383	0.004***
Wholesale and Retail Trades	0.134	0.338			

*** $\alpha = 0.01$, ** $\alpha = 0.05$ and * $\alpha = 0.1$.

Table 3
The coefficients of multiple linear test.

Factors	Unstandardized coefficients		Standardized coefficients			Collinearity statistics	
	B	Std. Error	Beta	t	Sig.	Tolerance	VIF
(Constant)	71.633	9.733					
Permanent Resident Population	.058	.022	1.019	2.601	.013	.082	12.223
Per capita GDP	−1.836	1.043	−.227	−1.759	.085	.752	1.330
Urbanization Rate	−5.848	16.109	−.051	−.363	.718	.627	1.595
Production and Distribution of Electricity, Gas and Water	−9.533	8.254	−.578	−1.155	.254	.050	19.914
Construction	.322	.584	.120	.551	.584	.266	3.765
Education	−.992	3.282	−.288	−.302	.764	.014	72.063
Public Management and Social Organization	.742	2.556	.208	.290	.773	.025	40.771

Fig. 11. The spatial relationship between $PM_{2.5}$ concentrations and selected variables in the BRUA.

- (1) The $PM_{2.5}$ concentrations had a negative relationship with GDP per capita (Fig. 11a). The GDP per capita, one of the macro-economy indicators, is widely used to reflect economic development levels and people's living standards. Results showed that 43 out of 53 cities in the BRUA had a negative relationship with GDP per capita, with an average coefficient of -1.8 , that is to say, an increment of 10,000 yuan GDP per capita would cause a reduction of $1.18 \mu\text{g}/\text{m}^3$ in $PM_{2.5}$. In terms of spatial variation, Shandong and southern Hebei had a significant positive relationship with per capita GDP in 10 cities in the mountainous areas of both Beijing and northern Hebei, and coastal areas of Liaoning. The reason is that, $PM_{2.5}$ in BRUA is mainly concentrated in the southern part of Hebei province and western part of Shandong province, where the economy is under-developed with the evidence of its relatively low GDP per capita and level of industrialization. The industrial sectors are primarily based on heavy chemical industries featured by high energy consumption, high pollution yet low output. City clusters in Shandong Peninsula enjoy the sound economic development favored by its coastal location, thus achieving the lower $PM_{2.5}$ concentrations. The densely populated Beijing and its higher per capita GDP, as well as the semi-closed landform, aggregated the pollution of $PM_{2.5}$. With lower $PM_{2.5}$ concentrations and per capita GDP, northern Hebei and coastal Liaoning had excellent and good air quality. Therefore, there was a positive correlation between $PM_{2.5}$ concentrations and per capita GDP in these areas. As one of the most developed regions, the BRUA has entered post-industrialized society, with upgrading of industry structure, wide use of clean energy and information technology and a reduction in industrial waste gas emissions. In addition, with the increase of per capita GDP, urban residents are demanding a better quality of life, and society is gaining environmental awareness. Meanwhile, the government at all levels has increased its environmental protection budgets and monitoring capabilities. This indicates that China has entered a stage when GDP per capita is negatively correlated with $PM_{2.5}$ concentrations.
- (2) In terms of the urbanization rate, it is positively correlated with $PM_{2.5}$ concentrations (Fig. 11b). China is undergoing a rapid urbanization process. The BRUA is the core region of such development, with an urbanization rate of 63.81% in 2013, 10 percentage points higher than the average national level. The $PM_{2.5}$ concentrations had a positive correlation with per capita GDP in 28 out of the 53 cities, and the average relevant coefficient was 1.25, that is to say, a 1% increase in urbanization rate would raise $1.25 \mu\text{g}/\text{m}^3$ in $PM_{2.5}$. As for spatial distribution, the $PM_{2.5}$ concentrations had a positive correlation with per capita GDP in cities in Shandong, Liaoning and new areas in eastern Tianjin, as well as eastern and southern Hebei, suggesting that the rapid urbanization had a direct effect on $PM_{2.5}$, whereas there was a negative correlation between $PM_{2.5}$ and urbanization in the old districts of Beijing and Tianjin, and cities in the mountainous areas of northern Hebei, indicating that urbanization in these areas had made no contribution to $PM_{2.5}$. According to the *National New-Type Urbanization Plan (2014–2020)*, China will maintain rapid urbanization as a means of expanding domestic demand over the coming 10 years. Population growth, land use expansion, and urban construction in the process of rapid urbanization will lead to greater emissions of SO_2 , NO_x , and dust, which will raise $PM_{2.5}$ concentrations.
- (3) $PM_{2.5}$ concentrations have a positive relationship with the building industry (Fig. 11c). The process of rapid urbanization is the process of building development. Building can directly generate smoke and dust. In addition, the related industries (such as cement, iron, and steel) are also high energy-consuming sectors with a large amount of $PM_{2.5}$ emissions. The $PM_{2.5}$ concentrations have a positive relationship with the size of the population engaged in the building industry in 53 cities, with the average coefficient of 0.97, that is to say, an increment of 10,000 of the working population in the building industry would also advance $0.09 \mu\text{g}/\text{m}^3$ of $PM_{2.5}$. In terms of spatial distribution, the significant positive correlation was mainly found in the Bohai Rim economic zone, including Beijing, Tianjin, southeastern Hebei, most parts of Shandong and southwestern Liaoning. These rapidly developed regions concerning building, represented by the real estate and infrastructure sectors, have made great contributions to PM concentrations in the BRUA; while affected by the landforms, building developed slowly in Qingdao in Shandong, northern Hebei mountainous areas and northern Liaoning made less contribution to $PM_{2.5}$ concentrations as these areas were less affected by building.

southern Hebei as the core area, while low concentrations were situated along the coasts of the Bohai Sea and mountainous areas in northern Hebei. In terms of seasonal variation, winter and summer witnessed the largest and smallest $PM_{2.5}$ pollution extents respectively, with average extents in spring and autumn. In winter, 46 out of 88 days were above the standard. Xingtai, Baoding and Shijiazhuang had more than 72 days of above the standard, and 27 cities had an over-standard rate of 50% (44 days), which were widely distributed across the whole BRUA. Monthly variation was also one of the main features of $PM_{2.5}$ concentration. There were three pollution diffusion cycles from west to east, and cities had the most seriously polluted extent during January, February, November and December.

- (3) Cities in the BRUA had a significant spatial hot-spot of $PM_{2.5}$ concentration, with agglomeration degrees high in spring and low in summer. Beijing, Tianjin, and southern Hebei and northwestern Shandong were the top three High–High $PM_{2.5}$ concentrated regions. Excellent and good air quality

cities were mainly in the Shandong Peninsula, East Liaodong Peninsula and mountainous areas in northern Hebei. To get the detailed analysis results, $PM_{2.5}$ concentration data was studied on a monthly basis. Apart from May, all the monthly $PM_{2.5}$ concentrations manifested obvious agglomeration. Cities with high $PM_{2.5}$ concentrations during the whole year demonstrated an M-shaped cycle with two advances and two retreats in highly concentrated areas. Lower concentrated areas, such as the Shandong Peninsula, East Liaodong Peninsula and northern Hebei, presented an opposite situation.

- (4) The analysis results obtained through the GWR model showed that GDP per capita, the urbanization rate and construction of cities in the BRUA had obvious correlations with $PM_{2.5}$ concentration. Overall, $PM_{2.5}$ concentration showed a negative relationship with per capita GDP. An increment of 10,000 yuan GDP per capita would cause a reduction of $1.18 \mu\text{g}/\text{m}^3$ in $PM_{2.5}$. At present, the $PM_{2.5}$ concentrations had a positive relationship with the urbanization rate, and a 1%

increase in the urbanization rate would raise $1.25 \mu\text{g}/\text{m}^3$ in $\text{PM}_{2.5}$; $\text{PM}_{2.5}$ concentration had positive relationship with the building industry, and an increment of 10,000 of the working population in the building industry would also advance $0.97 \mu\text{g}/\text{m}^3$ of $\text{PM}_{2.5}$.

Acknowledgments

This study was primarily funded by the Major Program of the Natural Science Foundation of China (41590840, 41590842), and the State Key Program of National Natural Science Foundation of China (71433008) prepared by Fang C. L. and Wang Z. B. Support was also provided by the National Natural Science Foundation of China prepared by Fang C. L. (41371177), and the Natural Youth Science Foundation of China prepared by Wang Z. B. (41201168). A part of $\text{PM}_{2.5}$ Data was provided by the Sub Center of Data Integration and Modeling for Global Change.

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Further-reading

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