Spatio-temporal variation and influence factors of PM$_{2.5}$ concentrations in China from 1998 to 2014

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**Abstract**

Based on the remote sensing retrieval of PM$_{2.5}$ concentration data in the long-time series, both the linear regression and grey system correlation analysis methods were employed to analyze the spatial and temporal pattern, variation trend and the main influencing factors of PM$_{2.5}$ concentration in China from 1998 to 2014. The results showed that only 16.21%–24.67% of the land area in China PM$_{2.5}$ concentrations reached the annual average criterion value of 10 $\mu$g/m$^3$ set by the World Health Organization (WHO) in 1998–2014; the PM$_{2.5}$ concentrations were greater than 95 $\mu$g/m$^3$ mainly in Xinjiang Taklimakan Desert, west of Tianjin and the central region of Hebei. PM$_{2.5}$ concentration was less than 10 $\mu$g/m$^3$ mainly in Tibet, western Sichuan, northeastern Yunnan, Taiwan, northern Xinjiang, northern Inner Mongolia and northwest of Heilongjiang. High PM$_{2.5}$ concentration in the northwest of China was mainly affected by sand and dust, while it was mainly caused by human activities in the eastern region. Except for Taiwan, low PM$_{2.5}$ concentration areas were mainly located in the economically backward regions. The positive indicators in highly correlation with PM$_{2.5}$ concentration include the average temperature, the proportion of primary and secondary industry to GDP, industrial consumption, the proportion of investment in real estate development to GDP, SO$_2$ emissions and population density. The negative indicators in highly correlation with PM$_{2.5}$ concentration include the average precipitation, the proportion of the tertiary industry to GDP, and the greening coverage rate of the built-up areas.

1. Introduction

With the rapid development of economy and urbanization in China, a series of environmental problems have been brought about, especially the pollution of PM$_{2.5}$ (particulate matter with aerodynamic $\leq 2.5$ $\mu$g/m$^3$) (Geng et al., 2015; Tian et al., 2014; Wang et al., 2014a,b) has seriously affected the human health (Guan et al., 2014) and socio-economic development (Xie et al., 2016). It has become a serious obstacle to the sustainable development of Chinese cities, forcing the government to take control measures such as traffic restrictions (Wang et al., 2015), class suspension for students, factory production limitation, or even stopping production. It has also become a social concern and the focus of public opinion and academic research.

At present, the ground observation (Wang et al., 2014a,b; Zhang and Cao, 2015; Sun et al., 2016) and satellite remote sensing retrieval of data (Han et al., 2015; Zheng et al., 2016; Lin et al., 2013; Peng et al., 2016) are applied for the study of PM$_{2.5}$ concentration. The accuracy and time resolution of ground observation data are high, but the data from monitoring stations often cannot reflect the spatial variability of PM$_{2.5}$ concentration in the large area, especially in the mountainous areas with complex topography and highly populated cities with complicated underlying surface. The mean value of the data from the decentralized monitoring stations as the PM$_{2.5}$ concentration in the area may lead to systematic errors in assessing population exposure and health effects (Lin et al., 2016). Compared with the ground observation, the satellite remote sensing can quickly obtain PM$_{2.5}$ concentration of continuous surface in the large area, especially it has the vital significance for understanding the PM$_{2.5}$ pollution level in areas where the
monitoring stations have not been established. By the end of 2012, the national air pollution monitoring network has been established, but few monitoring stations, short construction time and lack of long-term observation data have been shown. Therefore, the satellite remote sensing retrieval of data is still an effective means to evaluate the PM$_{2.5}$ pollution level in the large area (Ma et al., 2015), especially for the variation trend analysis and evaluation of the PM$_{2.5}$ concentration, it is indispensable. The research on PM$_{2.5}$ concentration both at home and abroad mainly focused on element composition (Shaltout et al., 2013), source analysis (Huang et al., 2014; Jansen et al., 2014), health effect (Song et al., 2016), pollution control (Zhang et al., 2013) and so on. Although some scholars used the annual average or multi-year average to study PM$_{2.5}$ pollution pattern, there are relatively fewer studies and analysis on PM$_{2.5}$ concentration pattern, variation trend and influencing factors, because the PM$_{2.5}$ concentration data are difficult for acquisition in a large scale for a long term or the continuous monitoring has not been performed for the data at all. PM$_{2.5}$ pollution process is a very complex system process, the pollution source diversity is remarkable, which contains a large number of known and unknown information state, and it is a typical grey system (He et al., 2016).

Therefore, based on the remote sensing retrieval of PM$_{2.5}$ concentration data in the long-time series, data extraction and partition calculation, the spatial pattern of PM$_{2.5}$ concentration in China from 1998 to 2014 was analyzed. The linear regression method was employed to reveal the variation trend of PM$_{2.5}$ concentration. Finally, the grey correlation analysis method was adopted to analyze the correlation between PM$_{2.5}$ concentration and influencing indicators. Through the above methods, the main factors influencing PM$_{2.5}$ concentration change can be found in order to make targeted control and improve urban air quality, providing a scientific basis for China to choose a scientific path of new urbanization development and make policy on PM$_{2.5}$ pollution control.

2. Index system construction and data sources

2.1. PM$_{2.5}$ concentration impact index system construction

PM$_{2.5}$ is mainly originated from coal combustion, motor vehicle exhaust, road dust and biomass combustion (Cao, 2014), and its formation and changes are also affected by meteorological conditions and other factors. Therefore, 22 indexes (Table 1) were selected from four aspects of meteorological conditions, pollution sources, urbanization and industrial structure, corporate pollution control and technological progress, according to data availability principle as well as its pollution sources and influencing factors (He et al., 2016). Meteorological conditions include precipitation, average wind velocity, average temperature and average relative humidity to reflect the influence on PM$_{2.5}$ mass concentration; PM$_{2.5}$ pollution source indicators include industrial electricity consumption, proportion of fulfilled amount of investment in real estate development to GDP, sulfur dioxide emissions, smoke (dust) emissions, the total volume of annual bus passenger traffic, total road freight and public transport vehicles, reflecting the industrial production process and traffic-generated road dust, exhaust emissions. Urbanization and industrial structure include population density, area of built-up districts, per capita GDP, proportions of primary, secondary and tertiary industry to GDP, total green area and greening coverage rate of built-up area, to reflect the influence of urbanization process and socio-economic activities on PM$_{2.5}$ concentration. Corporate pollution control and technological progress include SO$_2$ removal, smoke (dust) removal and proportion of R&D expenditure to GDP, reflecting the intensity of corporate emission reduction and pollution control technology.

2.2. PM$_{2.5}$ concentrations data

Currently, there is a lack of publically available global remote sensing data relating to PM$_{2.5}$. van Donkelaar et al. (2006, 2010, 2015) estimate ground-level fine particulate matter (PM$_{2.5}$) by combining Aerosol Optical Depth (AOD) retrievals from the NASA MODIS, MISR, and SeaWiFS instruments with the GEOS-Chem chemical transport model, and subsequently calibrated to global ground-based observations of PM$_{2.5}$ using Geographically Weighted Regression (GWR). The global PM$_{2.5}$ concentration dataset had a spatial resolution of 10 km from 1998 to 2014. It is by far the most accurate PM$_{2.5}$ remote-sensing data set with the largest coverage and longest time span that is available, it has been validated and can be effectively applied on a national scale (Lee et al., 2012; de Sherbinin et al., 2014). The dataset can be directly downloaded from Atmospheric Composition Analysis Group at Dalhousie University (http://fizz.phys.dal.ca/~atmos/martin/?page_id=140). We used a subset of global PM$_{2.5}$ concentration dataset that covered China from 1998 to 2014 extracted from nc format by ArcGIS Soft.

Although, van Donkelaar et al. has validated the accuracy of the global annual PM$_{2.5}$ concentrations grids dataset based on the

<table>
<thead>
<tr>
<th>Meteorological conditions</th>
<th>Average relative humidity (1%) ($x_1$)</th>
<th>Precipitation (mm) ($x_2$)</th>
<th>Average wind velocity (m/s) ($x_3$)</th>
<th>Average temperature °C ($x_4$)</th>
<th>Total volume of annual bus passenger traffic (10,000 person) ($x_5$)</th>
<th>Total road freight (t) ($x_6$)</th>
<th>Public transport vehicles (m) ($x_7$)</th>
<th>Industrial electricity consumption (100 million kwh) ($x_8$)</th>
<th>Proportion of fulfilled amount of investment in real estate development to GDP (x9)</th>
<th>SO$<em>2$ removal (t) ($x</em>{10}$)</th>
<th>Smoke (dust) emissions (t) ($x_{11}$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>PM$_{2.5}$ pollution sources</td>
<td>Urbanization and industrial structure</td>
<td>Population density (person/km$^2$) ($x_{12}$)</td>
<td>Area of built-up districts (km$^2$) ($x_{13}$)</td>
<td>Per capita GDP (x$14$)</td>
<td>Proportion of primary industry to GDP (x$15$)</td>
<td>Proportion of secondary industry to GDP (x$16$)</td>
<td>Proportion of tertiary industry to GDP (x$17$)</td>
<td>Total green area (km$^2$) ($x_{18}$)</td>
<td>Greening coverage rate of built-up area ($x_{19}$)</td>
<td>SO$<em>2$ removal (t) ($x</em>{20}$)</td>
<td>Smoke (dust) removal (t) ($x_{21}$)</td>
</tr>
</tbody>
</table>

Note: + denotes the positive indicators and the rest are negative indicators.
agreement between satellite-derived estimates and ground-based measurements (van Donkelaar et al., 2010). However, considering that the relationship between AOD-PM2.5 can differ by space and countries, it was still necessary to evaluate the reliability of the dataset for the specific area of China (Luo et al., 2017). The Ministry of Environmental Protection of China (MEP) published the PM2.5 concentration over ground observation sites from 2012. We collected Chinese ground-based PM2.5 measurements of 68 sample points in 2013 year and spatial distribution of these sample points are shown in Fig. 1(a). Furthermore, according to the sample points, the corresponding satellite-derived values of PM2.5 concentrations data were calculated. Also, the linear correlation between “PM2.5 Ground-based Values” and “PM2.5 Satellite-derived Values” is shown in Fig. 1(b). A significant overall agreement is found ($R^2 = 0.817$), which indicated that the satellite-derived PM2.5 concentration data were reliable.

2.3. Socioeconomic data

In order to ensure the continuity of data, the data of PM$_{2.5}$ pollution sources, and urbanization and industrial structure indicators from 274 cities in China during 2003–2014 were collected on a prefecture-level city scale. The data are sourced from China City Statistical Yearbook (2003–2015) (http://tongji.cnki.net/ks55/Navi/NaviDefault.aspx). Public transport vehicles = Buses operated at the end of the year + Number of taxis at the end of the year.

2.4. Meteorological data

The meteorological data are derived from China Meteorological Data Network (http://data.cma.cn), including four indicators of average daily temperature, cumulative precipitation, average wind velocity and average relative humidity.

3. Methods

3.1. Unitary linear regression analysis

Unitary linear regression analysis was used to examine the variation trend of PM$_{2.5}$, and the fitting slope could reflect the variation trend. The formula is:

$$\text{Slope} = \frac{\sum_{i=1}^{n} i \cdot PM_{2.5} - \frac{1}{n} \left( \sum_{i=1}^{n} i \right) \left( \sum_{i=1}^{n} PM_{2.5} \right)}{\sum_{i=1}^{n} i^2 - \frac{1}{n} \left( \sum_{i=1}^{n} i \right)^2}$$

In which PM$_{2.5}$ is the grid unit PM$_{2.5}$ concentrations, $n$ is the time span, and $i$ is the time unit. slope $>0$, meaning that PM$_{2.5}$ increased over time; slope $<0$, meaning that PM$_{2.5}$ decreased over time; The size of slope could reflect the speed of increase or decrease. F test was used to conduct significance test. The increased or decreased trend was significant if the slope $p < 0.05$, and if $p < 0.01$, it would be highly significant.

3.2. Grey correlation analysis method

The grey correlation analysis method is proposed by Ju-Long, (1982), the calculation steps go as follows:

First, specify the reference sequence $x_0(t)$ and compared sequence $x_i(t)$, $t$ represents point or time, they are given by the followed formula respectively:

$$x_0(t) = \{x_0(1), x_0(2), \cdots, x_0(n)\}, \quad t = 1, 2, \cdots, m$$

$$x_i(t) = \{x_i(1), x_i(2), \cdots, x_i(n)\}, \quad i = 1, 2, \cdots, n$$

where $m$ is the number of point or time, $n$ is the number of compared sequence.

Given that there may be different dimension between reference sequence and compared sequences, the standardization processing is need before going to the next step.

Essentially, correlation coefficient is the geometrical differences between curves. Hence, the size of differences becomes the measurement scale of correlation. Correlation coefficient calculate correlation coefficient and correlation degree. Correlation coefficient is calculated by the followed formula:

$$\xi_i(k) = \frac{\min_k \min_i |x_0(k) - x_i(k)| + \rho \max_k \max_i |x_0(k) - x_i(k)|}{|x_0(k) - x_i(k)| + \rho \max_k \max_i |x_0(k) - x_i(k)|}$$

where, $\xi_i(k)$ is the relative difference between reference sequence (or curve) and compared sequence (or curve), which was regarded as the correlation coefficient between $x_i$ and $x_0$ at point $k$ (or time

Fig. 1. (a) The ground-based PM$_{2.5}$ measurements in 2013 collected from urban air quality monitoring data undertaken by China’s National Environmental Monitoring Centre and (b) linear correlation of the two datasets (PM$_{2.5}$ ground-based values and satellite-derived values).
Correlation degree is the average value of correlation coefficient, calculated by the followed formula:

\[
\gamma_i = \frac{1}{n} \sum_{k=1}^{n} \xi_i(k)
\]

where \(\gamma_i\) is the correlation degree between reference sequence \(x_0(t)\) and compared sequence \(x_i(t)\). \(\gamma_i\). The bigger the \(\gamma_i\), the stronger the impact of factor and the more significant the contribution, and vice versa. Generally, the correlation degree is low if 0<\(\gamma_i\)≤0.30, is moderate if 0.30<\(\gamma_i\)≤0.60, and is strong if 0.60<\(\gamma_i\)≤1.0.

In this study, the reference sequence referred to the PM2.5 data and the compared sequence referred to the influence index in China, and the correlation degree in period from 2003 to 2014 were calculated.

4. Results

4.1. Time variation characteristics of PM2.5 concentrations

According to China’s air quality standards, the annual average PM2.5 concentration is divided into five levels, and Fig. 2 reflects the proportion of different levels to the total area in different years during 1998–2014. As can be seen from Fig. 2, the concentration of PM2.5 in China was less than 10 \(\mu g/m^3\) in 1998–2014, accounting for 16.21%–24.67% of the total area, with the maximum in 1999 and the minimum in 2008; 10–35 \(\mu g/m^3\) accounted for 45.74%–54.27% of the total area, with the maximum in 1999 and the minimum in 2006; 35–75 \(\mu g/m^3\) accounted for 18.17%–31.37% of the total area, with the maximum in 2002 and the minimum in 2006; 75–95 \(\mu g/m^3\) accounted for 0.02%–5.10% of the total area, with the maximum in 2007 and the minimum in 2000; 95 \(\mu g/m^3\) and above accounted for 0.0%–2.58% of the total area, with the maximum in 2010, and the PM2.5 concentration in 2000 and 2001 was not greater than 95 \(\mu g/m^3\). From Fig. 2, in addition to relatively stable change of level greater than 95 \(\mu g/m^3\) from 1998 to 2014, the changes of the other PM2.5 concentration levels were fluctuating. PM2.5 concentration was mainly between 10 and 35 \(\mu g/m^3\) in China, accounting for about half of the land area, 61.95%–78.93% of the land area reached the annual average limit of level II (35 \(\mu g/m^3\)) according to the ambient air quality standard (GB3095-2012), and only 16.21%–24.67% reached the annual average criterion value of 10 \(\mu g/m^3\) by the World Health Organization.

![Area proportion of China under different PM2.5 concentrations from 1998 to 2014.](image)

4.2. Spatial distribution characteristics of PM2.5 concentrations

Fig. 3 shows the spatial distribution of the maximum, minimum and average of PM2.5 concentration in China from 1998 to 2014. From the maximum figure, the regions with high PM2.5 concentration were seriously polluted areas, mainly in the Taklimakan Desert of Xinjiang and the Beijing-Tianjin-Hebei Economic Zone in North China. PM2.5 concentration was greater than 95 \(\mu g/m^3\) in the Xinjiang Taklimakan Desert, west of Tianjin and the central Hebei. Although the minimum concentration of PM2.5 in these areas did not exceed 95 \(\mu g/m^3\), it was also higher than that in other areas, ranging from 35 to 75 \(\mu g/m^3\). In the maximum figure, 10 \(\mu g/m^3\) and below, 10–35 \(\mu g/m^3\), 35–75 \(\mu g/m^3\), 75–95 \(\mu g/m^3\) as well as 95 \(\mu g/m^3\) and above accounted for 10.48%, 42.98%, 39.43%, 4.26% and 2.84% of the total area respectively. From the minimum figure, PM2.5 concentration was less than 10 \(\mu g/m^3\) mainly in Tibet, western Sichuan, northeastern Yunnan, Taiwan, northern Xinjiang, northern Inner Mongolia and northwest of Heilongjiang, 10 \(\mu g/m^3\) and below, 10–35 \(\mu g/m^3\), 35–75 \(\mu g/m^3\) and 75–95 \(\mu g/m^3\) accounted for 27.58%, 57.15%, 15.27% and 0.004% of the total area respectively. The multi-year average PM2.5 concentration was calculated, reflecting the general level of PM2.5 concentration during the study period. From the average figure, the distribution of high and low PM2.5 concentration was basically consistent with the maximum and minimum figures, further confirming the basic pattern of the spatial distribution of PM2.5 concentration in China, where 10 \(\mu g/m^3\) and below, 10–35 \(\mu g/m^3\), 35–75 \(\mu g/m^3\), 75–95 \(\mu g/m^3\) as well as 95 \(\mu g/m^3\) and above accounted for 18.70%, 50.54%, 27.97%, 2.79% and 0.004% of the total area respectively. It can be shown from the above analysis, the spatial distribution of PM2.5 concentration in China was obviously different, and the high concentration was mainly affected by sand and dust in the northwestern China, while it was mainly caused by human activities in the eastern part. Except for Taiwan, the low PM2.5 concentration regions were mainly located in economically backward areas.

4.3. PM2.5 concentrations variation trend analysis

The annual average PM2.5 concentration and time were used for linear regression analysis, and the regression coefficient characterized the spatial variation trend of PM2.5 concentration during 1998–2014. The slope was divided into three levels according to the positive and negative change respectively, where slope ≤ −1 indicated severe decrease, −1<slope ≤ −0.5 for moderate decrease, −0.5 < slope<0 for slight decrease, 0 < slope<0.5 for slight increase, 0.5 < slope<1 for moderate increase and slope>1 for severe increase. As shown in Fig. 4, slope values were between −1.1 and 2.2 in the past 17 years, and the variation trend of PM2.5 concentration in China exhibited significant spatial distribution difference, with slope>0 accounting for 76.86% of the total area in North China Plain, Yangtze River Delta region, central China, southwest region, Xinjiang Taklimakan Desert and Qinghai, while slope<0 accounting for 23.14% of the total area in the Loess Plateau, northeast of Heilongjiang and Inner Mongolia, the southeast coastal areas and Hainan. PM2.5 concentration presented a rapid growth in Xinjiang Taklimakan Desert, Qaidam Basin and the eastern part of the North China Plain. The spatial distribution and area of different growth types are as shown in Fig. 4 and Table 2. The increasing trend of PM2.5 concentration from 1998 to 2014 was much greater than the decreasing trend.

The F-test method was employed to examine the significant change of PM2.5 concentration (P<0.05). As shown in Fig. 5, the change trend of PM2.5 value was statistically significant in only 27.3% of the land area, and the increasing trend of PM2.5 concentration was subject to significance testing in Qinghai, Tibet,
Xinjiang, Shaanxi, Hubei, Shandong, Hebei, Beijing, southwest of Yunnan and the central region of Guizhou, with the decreasing trend in Hainan, Fujian, Ningxia, Loess Plateau at junction of Shaanxi and Inner Mongolia. Except for Hebei, Shandong, Beijing and Tianjin in the eastern North China Plain, the PM$_{2.5}$ concentration increase was significant in the mostly central and western regions, indicating that the rising trend of PM$_{2.5}$ concentrations in the central and western parts of China had a statistical significance.

Government policy-makers should be alert to this phenomenon, and take emphasis on PM$_{2.5}$ pollution in the central and western regions as the same in the eastern developed areas to adopt low-carbon and environmentally friendly economic development model to prevent the deterioration of PM$_{2.5}$ pollution wherein. In addition, compared with other regions, the North China Plain was a typical high-value region of PM$_{2.5}$ concentration in China, and the analysis results showed a significant upward trend. Therefore, the PM$_{2.5}$ pollution control efforts shall be further strengthened. It can also be seen from the above analysis, the rising PM$_{2.5}$ concentration trend was shown on a regional, or even national scale. Thus, control policies shall be developed not only for a particular city but also
Fig. 4. Trend of PM$_{2.5}$ concentrations in China during 1998–2014.

Table 2
Proportion of provinces in China under different slope classification (%).

<table>
<thead>
<tr>
<th>Province</th>
<th>Slope ≤ -1</th>
<th>-1 &lt; Slope ≤ -0.5</th>
<th>-0.5 &lt; Slope ≤ 0</th>
<th>0 &lt; Slope ≤ 0.5</th>
<th>0.5 &lt; Slope ≤ 1</th>
<th>Slope &gt; 1</th>
</tr>
</thead>
<tbody>
<tr>
<td>China</td>
<td>0.07</td>
<td>1.07</td>
<td>22.08</td>
<td>58.09</td>
<td>12.69</td>
<td>6</td>
</tr>
<tr>
<td>Beijing</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>Tianjin</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>Hebei</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>0.08</td>
<td>0.70</td>
<td>0.78</td>
</tr>
<tr>
<td>Henan</td>
<td>–</td>
<td>–</td>
<td>0.11</td>
<td>0.41</td>
<td>1.07</td>
<td>0.09</td>
</tr>
<tr>
<td>Shandong</td>
<td>–</td>
<td>–</td>
<td>0.01</td>
<td>0.23</td>
<td>0.65</td>
<td>0.72</td>
</tr>
<tr>
<td>Inner Mongolia</td>
<td>–</td>
<td>0.43</td>
<td>8.36</td>
<td>4.66</td>
<td>–</td>
<td>–</td>
</tr>
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<td>0.01</td>
<td>3.19</td>
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<td>–</td>
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<td>Jilin</td>
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<td>–</td>
<td>0.51</td>
<td>1.69</td>
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<td>Liaoning</td>
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<td>–</td>
<td>0.67</td>
<td>0.95</td>
<td>–</td>
<td>–</td>
</tr>
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<td>0.80</td>
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<td>–</td>
<td>0.07</td>
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<td>0.48</td>
<td>0.49</td>
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<td>–</td>
</tr>
<tr>
<td>Anhui</td>
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<td>–</td>
<td>0.49</td>
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<tr>
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<td>–</td>
</tr>
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<td>–</td>
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<tr>
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<td>–</td>
<td>2.06</td>
<td>–</td>
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<td>–</td>
</tr>
<tr>
<td>Hainan</td>
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<td>–</td>
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</tr>
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<td>Guizhou</td>
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<td>0.05</td>
<td>1.61</td>
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<tr>
<td>Yunnan</td>
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<td>–</td>
<td>0.06</td>
<td>3.41</td>
<td>0.11</td>
<td>–</td>
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<td>–</td>
<td>0.79</td>
<td>0.01</td>
<td>–</td>
</tr>
<tr>
<td>Sichuan</td>
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<td>0.53</td>
<td>4.04</td>
<td>0.14</td>
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<td>11.04</td>
<td>0.07</td>
<td>–</td>
</tr>
<tr>
<td>Shaanxi</td>
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<td>0.11</td>
<td>0.50</td>
<td>0.57</td>
<td>0.93</td>
<td>0.01</td>
</tr>
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<td>–</td>
<td>0.06</td>
<td>0.87</td>
<td>0.80</td>
<td>–</td>
</tr>
<tr>
<td>Gansu</td>
<td>–</td>
<td>0.15</td>
<td>1.11</td>
<td>2.63</td>
<td>0.43</td>
<td>–</td>
</tr>
<tr>
<td>Ningxia</td>
<td>0.01</td>
<td>0.36</td>
<td>0.11</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>Qinghai</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>3.74</td>
<td>3.17</td>
<td>0.50</td>
</tr>
<tr>
<td>Xinjiang</td>
<td>–</td>
<td>–</td>
<td>1.82</td>
<td>8.65</td>
<td>3.71</td>
<td>4.11</td>
</tr>
<tr>
<td>Taiwan</td>
<td>–</td>
<td>–</td>
<td>0.28</td>
<td>0.05</td>
<td>–</td>
<td>–</td>
</tr>
</tbody>
</table>
from the regional or even national perspective.

4.4. Correlation analysis of PM$_{2.5}$ concentrations and influence index

There are many intricate factors influencing PM$_{2.5}$ concentration. According to the index system constructed in Table 1, the grey correlation between PM$_{2.5}$ concentration and influence index was calculated. The correlation ($\gamma_i$) values between 22 indexes and PM$_{2.5}$ concentration are shown in Table 3, and it can be seen that their correlation values are larger at moderate or strong level, fully indicating the evaluation factors have an important impact on the PM$_{2.5}$ concentration change, and also showing the selection of each index factor was relatively reasonable. The meteorological condition is the external cause to the formation of PM$_{2.5}$ pollution, and the correlation of indexes from high to low is as follows: the average precipitation, average wind velocity, average air temperature and average relative humidity. The research has shown that the precipitation has the effect of flushing on dust particles in PM$_{2.5}$ (Cao, 2014), the wind velocity has a significant effect on the diffusion of PM$_{2.5}$ (Han et al., 2016), the temperature has a catalytic effect on the chemical reactions of PM$_{2.5}$ precursor pollutants (Zhang and Cao, 2015), and high humidity conditions will promote the formation of nitrate and secondary organic aerosols (Wang et al., 2016). Excessive emission is the root cause of PM$_{2.5}$ pollution. The correlation of PM$_{2.5}$ pollution source indexes is listed below from high to low: the proportion of fulfilled amount of investment in real estate development to GDP, SO$_2$ emission, industrial electricity consumption, public transport vehicles, the total volume of annual bus passenger traffic, total road freight and smoke (dust) emissions; the correlation of urbanization and industrial structure indexes is shown as follows from high to low: the proportion of tertiary industry to GDP, the proportion of secondary industry to GDP, population density, greening coverage rate of the built-up areas, per capita GDP, area of built-up districts and total green area. Construction and emissions from freight automobiles are the main sources of dust emissions from transportation. Industrial electricity consumption and the proportion of secondary industry to GDP represent the scale and volume of industrial production. Emissions of industrial exhaust gas and smoke (dust) are one of the main sources of PM$_{2.5}$ pollution, while the green area can inhibit in reducing the concentration of PM$_{2.5}$. The correlation of corporate pollution control and technological progress indexes is exhibited below from high to low: the proportion of R&D expenditure to GDP, SO$_2$ removal and removal of industrial dust.

In order to avoid the selection of a large area, resulting in the instability of system analysis, the national seven regions were subject to grey correlation calculation according to the traditional Chinese regional zoning (Luo et al., 2017), with the results as shown in Table 3. From Table 3, it can be seen that the total precipitation, the average wind velocity, the proportions of primary, secondary and tertiary industry to GDP, the proportion of fulfilled amount of investment in real estate development to GDP, population density, SO$_2$ emission and greening coverage rate of built-up areas have strong correlation with PM$_{2.5}$ concentration in seven regions. Per capita GDP and relative humidity are also highly correlated with PM$_{2.5}$ concentration in the other six regions except for the northwest region. There are differences in correlation between the remaining indexes and PM$_{2.5}$ concentration in different regions, fully showing that the meteorological conditions, PM$_{2.5}$ pollution sources, urbanization process, efforts of corporate pollution emission control, technology, etc. have different impact on PM$_{2.5}$ concentration in different regions.

The results of the above analysis show that the grey correlation model analysis method can effectively analyze the main index factors that influence the spatial distribution of PM$_{2.5}$ concentration. The external causes, such as the total precipitation and
average wind velocity are the main influencing factors of PM$_{2.5}$ concentration. The internal causes, such as proportions of primary, secondary and tertiary industry to GDP, the proportion of fulfilled amount of investment in real estate development to GDP, population density, SO$_2$ emission and greening coverage rate of the built-up areas are the main influencing factors of PM$_{2.5}$ concentration. Therefore, the regional joint prevention and control (Liu et al., 2015), rational control of the urban population size, adjustment of the industrial structure, reduction of corporate pollution emissions, improvement of urban greening coverage rate of built-up areas and technological level should be emphasized in the treatment and control of PM$_{2.5}$ concentration.

### Table 3

<table>
<thead>
<tr>
<th>Influence index</th>
<th>Whole Country</th>
<th>Southwest China</th>
<th>Northwest China</th>
<th>South China</th>
<th>Central China</th>
<th>East China</th>
<th>North China</th>
<th>Northeast China</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average relative humidity</td>
<td>0.61</td>
<td>0.77</td>
<td>0.72</td>
<td>0.67</td>
<td>0.67</td>
<td>0.71</td>
<td>0.71</td>
<td>0.38</td>
</tr>
<tr>
<td>Precipitation</td>
<td>0.58</td>
<td>0.66</td>
<td>0.62</td>
<td>0.58</td>
<td>0.58</td>
<td>0.65</td>
<td>0.67</td>
<td>0.38</td>
</tr>
<tr>
<td>Average temperature</td>
<td>0.58</td>
<td>0.67</td>
<td>0.62</td>
<td>0.58</td>
<td>0.59</td>
<td>0.62</td>
<td>0.62</td>
<td>0.38</td>
</tr>
<tr>
<td>Average wind velocity</td>
<td>0.58</td>
<td>0.67</td>
<td>0.62</td>
<td>0.58</td>
<td>0.59</td>
<td>0.62</td>
<td>0.62</td>
<td>0.38</td>
</tr>
<tr>
<td>Average relative humidity</td>
<td>0.58</td>
<td>0.67</td>
<td>0.62</td>
<td>0.58</td>
<td>0.59</td>
<td>0.62</td>
<td>0.62</td>
<td>0.38</td>
</tr>
<tr>
<td>Average temperature</td>
<td>0.58</td>
<td>0.67</td>
<td>0.62</td>
<td>0.58</td>
<td>0.59</td>
<td>0.62</td>
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</tr>
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<td>Average wind velocity</td>
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<td>0.67</td>
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<td>0.58</td>
<td>0.59</td>
<td>0.62</td>
<td>0.62</td>
<td>0.38</td>
</tr>
</tbody>
</table>

### 5. Discussion

Social and economic development is a key factor in the deterioration of air quality, and meteorological conditions have a significant effect on its formation, distribution, maintenance and change. A broad consensus has been reached, and many studies have confirmed this (Zhang et al., 2013; Lin and Wang, 2016; Luo et al., 2017). From the analysis results of this study, the growth trend of PM$_{2.5}$ concentration in China was regional and even national, while a significant growth trend was exhibited in the North China Plain and the central and western regions. This result was consistent with the statistics by employing monitoring site data of Greenpeace (http://www.greenpeace.org.cn/city-ranking-2016-q1/). PM$_{2.5}$ data of remote sensing inversion were adopted herein, so that the time series were longer and more persuasive. The PM$_{2.5}$ concentration was significantly increased in the North China Plain and the central & western regions, because Beijing-Tianjin-Hebei, Yangtze River Delta and the Pearl River Delta were key areas in China’s action plan of air pollution prevention and control, and more strict PM$_{2.5}$ governance goals have been set up. On the other hand, many restrictions imposed by the central government on haze in the east would lead to the transfer of some polluting enterprises to the central and western regions that were not subject to heavy pollution. The results of grey relational analysis also showed stronger correlation between PM$_{2.5}$ concentration and the secondary industry proportion of GDP in southwest, northwest and central China than in south China and east China. In the traditional heavy industry base in north and northeast China, the proportion of the secondary industry has been relatively large. As can be seen from Table 3, except for the average wind velocity and population density, the grey correlation values are basically the same in the southwest and northwest regions, but the PM$_{2.5}$ concentration in the northwest region is obviously higher than that in the southwest region, indicating a considerable portion from the dust aerosol in the northwest region. Through the observation data analysis of 88 monitoring stations in Xinjiang from 2000 to 2011, the Taklimakan Desert and the south source had a high incidence of sand and dust weather, and the number of annual dusty days in southern Xinjiang was 2.7 times that of northern Xinjiang (Yuan-An et al., 2013), so it was China’s most serious sandstorm area. As the economy of South China, Central China, East China, North China and Northeast China was relatively developed in eastern and central regions, the overall concentration of PM$_{2.5}$ in South China was lower than the above areas. From the industrial structure, the proportion of secondary industry to GDP in North China, Central China and Northeast China was highly correlated, followed by East China, with the minimum in South China, while the grey correlation of SO$_2$ and smoke (dust) removal in South China was higher than that in the other areas mentioned above, indicating that the proportion decrease of secondary industry and emission reduction by the corporate could significantly reduce the regional PM$_{2.5}$ concentration.

The above analysis results also showed that the different regions...
were affected by the complex factors such as the regional resources and environment, and the influence direction and intensity of social & economic development and meteorological conditions on PM$_{2.5}$ were also different significantly. Although the current economic development in China will increase the concentration of PM$_{2.5}$, our discussion on the means to curb the deterioration of air quality, does not mean to fully curb economic development. Therefore, through the comparative analysis of socio-economic factors and PM$_{2.5}$, the regional differences and the common development model of population, social economy and ecological environment should be taken into account comprehensively in the development of PM$_{2.5}$ emission reduction policy on the basis of regional development status and resource environment, to make a reasonable control of urban population size, adjust the industrial structure, reduce enterprise pollution emissions and increase the green coverage in urban built-up areas. In the process of pollution management and control, the regional joint prevention and control should be emphasized (Liu et al., 2015), to minimize the negative impact caused by the economic development.

6. Conclusions

Based on the remote sensing retrieval of PM$_{2.5}$ concentration data in the long-time series, both the linear regression and grey system correlation analysis methods were employed to analyze the spatial and temporal pattern, variation trend and the main influencing factors of PM$_{2.5}$ concentration in China from 1998 to 2014.

1. 61.95%–78.93% of the land area reached the annual average level of II (35 μg/m$^3$) according to the ambient air quality standard (GB3095-2012), and only 16.21%–24.67% reached the annual average criterion value of 10 μg/m$^3$ by the World Health Organization from 1998 to 2014.

2. PM$_{2.5}$ concentration was greater than 95 μg/m$^3$ in the Xinjiang Talikman Desert, west of Tianjin and the central Hebei. PM$_{2.5}$ concentration was less than 10 μg/m$^3$ mainly in Tibet, western Sichuan, northeastern Yunnan, Taiwan, northern Xinjiang, northern Inner Mongolia and northwest of Heilongjiang.

3. The areas presenting a rising trend of PM$_{2.5}$ concentrations were much larger than those presenting a decrease trend. PM$_{2.5}$ concentration exhibited a significant rising trend in central and western regions as well as North China Plain.

4. The positive indicators in highly correlation with PM$_{2.5}$ concentration include the average temperature, the proportion of primary and secondary industry to GDP, industrial consumption, the proportion of fulfilled amount of investment in real estate development to GDP, SO$_2$ emissions and population density. The negative indicators in highly correlation with PM$_{2.5}$ concentration include the average precipitation, the average wind velocity, the proportion of the tertiary industry to GDP, and the greening coverage rate of the built-up areas.

Acknowledgments:

This work was supported by the Guizhou Province Science and Technology fund (LKT[2012]07;25).

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