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Assessment of Urban Air Pollution and Spatial Spillover Effects in China: Cases of 113 Key Environmental Protection Cities

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Abstract: With rapid urbanization and energy consumption, environmental pollution and degradation have become increasingly serious problems in China. At the beginning of 2013, China implemented new ambient air quality standards (GB 3095-2012) in which the concentration of six pollutants including $PM_{2.5}$, ozone, carbon monoxide, PM_{10}, sulfur dioxide and nitrogen dioxide were monitored. This study gathered annual air pollutant concentration data for the six pollutants in 113 key environmental protection cites throughout China in 2014 and 2015 to explain spatial patterns of urban air pollution. Based on the Kernel density estimation method, spatial hotspots of air pollution were illustrated through which spatial cluster of each pollutants could be plotted. By employing an entropy evaluation system, urban air quality was assessed in terms of the six atmospheric pollutants. We conclude that, in general, CO and SO_2 were two important pollutants in most Chinese cities, but this varied greatly among cities. The assessment results indicate that cities with the worst air quality were mainly located in northern and central provinces, dominantly in the Beijing-Tianjin-Hebei metropolitan area. Regression modeling showed that a combination of meteorological factors and human-related determinants, to say specifically, industrialization and urbanization factors, greatly influenced urban air quality variation in China. Results from spatial lag regression modeling confirmed that air pollution existed obvious spatial spillover effects among key cities. The spatial interdependence effects of urban air quality means that Chinese municipal governments should strengthen regional cooperation and deepen bilateral collaboration in terms of air regulation and pollution prevention.

Key words: urban air quality; entropy assessment; spatial spillover; China

1 Introduction

It is well acknowledged that the economic reforms and opening up process in China since 1978 has greatly promoted the accumulating growth of urban areas and economic development. Meanwhile, the increasingly serious environmental problems have resulted from urbanization have gained a lot of attention. Air pollution events and serious hazy weather have brought about huge impacts on public health and social-economic activities. For instance, ambient particulate matter pollution has a close association with human deaths according to the World Health Organization Global Burden of Disease project (WHO, 2012). Recent research has shown that a substantial number of diseases have a close connection to the severity of air pollution (Chen *et al*., 2016; Liu *et al*., 2017a; Liu *et al*., 2016; Qin *et al*., 2017; Yang *et al*., 2016). Accordingly, the central government of China has realized that it is pressing to address air pollution problems, especially in densely populated urban areas. At the beginning of 2013, China implemented a new ambient air quality standard (GB 3095-2012), in which $PM_{2.5}$, ozone and carbon monoxide concentrations were included in the monitoring of urban ambient air quality in addition to PM_{10}, sulfur dioxide, and nitrogen dioxide (Min-

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istry of Environmental Protection, 2012). Meanwhile, a brand-new air quality index (AQI), including six air pollutants (PM_{10}, sulfur dioxide, nitrogen dioxide, carbon monoxide, $PM_{2.5}$ and ozone) was released. The MEP's AQI is based on Chinese Ambient Air Quality Standards, and is measured as the maximum pollution sub-AQI of all pollutants (MEP, 2012), which reflects the air quality of a city.

Since the release of the new ambient air quality standards, a number of papers have concerned urban air quality based on different study areas. At a national scale, Chen *et al*. provided an evaluation of national air qualities for major cities under the new NAAQS-2012 compared to the previous NAAQS-1996 and argued that the new standard had brought stricter requests for ambient air quality (Chen *et al*., 2015). At the same time, Lin *et al*. employed spatial effect models to explore the social-economic factors of urban air pollution based on air quality monitoring data for 161 sample cities in 2013 and 2014, whose results showed obvious spatial heterogeneity in the connections between determinants and air quality (Lin and Wang, 2016). At a regional scale, Wang *et al*. analyzed the correlation between air quality and emission control measures in the Pearl River Delta (Wang *et al*., 2016a). Chen analyzed characteristics of $PM_{2.5}$ at a rural site in the Northern China Plain (Chen *et al*., 2017). Fang *et al*. illustrated significant spatial differentiation and clustering pattern of $PM_{2.5}$ within northern and southern China based on observed concentration data from 190 cities in 2014 (Fang *et al*., 2016). These studies have analyzed the comprehensive air condition in some cities or part of specific regions, however, the fundamental distribution patterns of different pollutants at a national scale have not been explored in depth.

To evaluate urban air quality, it is important to choose an appropriate evaluation model, which has been discussed in academic literature for many years. The AQI (Air Quality Index) commonly used from MEP is calculated according to the largest particle concentration among several kinds of pollutants. However, this AQI cannot indicate the total air pollution status for it does not include a variety of pollutants in urban ambient. This method has been criticized because it does not reveal the overall situation of urban air pollution. Accordingly, adaption and improvement of AQI are worth studying. A number of studies in recent years have improved the AQI through developing a variety of new air pollution indexes and empirical test, such as considering many pollutant concentrations, considering the effect of health, and considering various influencing fuzzy factors (Khanna, 2000; Kyrkilis *et al*., 2007; WANG *et al*., 2016b). Wang *et al*. defined a term called the Environmental Quality Index (EQI) based on the human feelings of ambient air quality, reflecting the real sentiment approaching real conditions (Wang *et al*., 2017b). Kyrkilis *et al*. followed the idea of Swamee and Tyagi (Swamee and Tyagi, 1999) and developed an aggregate air quality index (AAQI) to estimate air pollution exposure. Hu *et al*. calculated the AAQI and health-risk based air quality index (HAQI) based on data collected in six megacities of China (Beijing, Shanghai, Guangzhou, Shijiazhuang, Xi'an, and Wuhan) during 2013 to 2014 (Hu *et al*., 2015). However, these methods have their limitations at a different degree, especially when the constants and threshold values determine the value of AAQI and HAQI, the results of the study will be greatly affected (Kyrkilis *et al*., 2007). Considering that different kinds of the composite index have inherent advantages and disadvantages, how to develop a new composite index is worth further studying for academic literatures.

Regarding spatial spillover effects, a large number of researchers have focused on the impact of natural factors on air pollution, including meteorological condition, climate change and air flow (Adams *et al*., 2005; Lu and Han, 2014; Tai *et al*., 2010; Wang and Liu, 2016). Some research has argued that socioeconomic factors have greatly affected air quality. For instance, Wang *et al*. investigated the correlation between road patterns and $PM_{2.5}$ pollution in Beijing and suggested to increase the number of branch and secondary roads to decrease $PM_{2.5}$ concentrations (Wang *et al*., 2017a). Zou *et al*. focused on the significant role of LUCC (urban land use/cover change) on PM_{10} concentration variation in the region of Changsha-Zhuzhou-Xiangtan, based on the data of simulated PM_{10} surfaces within this area in 2006 and 2013 (Zou *et al*., 2016). Zhou *et al*. explored the temporal-spatial characteristics of typical PM pollution events in 2013 and discussed the risk factors of PM pollution in Beijing-Tianjin-Hebei and surrounding areas (Zhou *et al*., 2016). These researches paid much attention to factors influencing air quality at a certain area. Comparatively speaking, the overall situation of different pollutants has not been well illustrated and so here we attempted to explore determinants of the main six air pollutants at a national scale.

We constructed a comprehensive index of urban air quality (CAQI) to reveal the overall situation of urban air pollution by combining the six main air pollutants. The CAQI is a method that calculates the weight of each air pollutant based on the entropy method, which considers all main pollutant concentrations in the AQI. Furthermore, we attempted to explore the spatial agglomeration characteristics of urban air quality in China and examine the spatial spillover effects and important effects of various determinants, both of which will significantly contribute to our understanding of spatial evolution for urban air quality in China. What's more, this study is expected to provide a scientific reference to carry out targeted pollution control measurements.

2 Materials and methods

2.1 Sample cities and data sources

This study selected the country of China as the study area, and considering the availability of data, we chose the 113 key environmental protection cites throughout China as sample cities. The 113 cities were put forward from the 11th Five-Year Plan, which aimed to construct a national environment supervision system and promote air regulation and pollution prevention. The spatial distribution of sample cities is shown in Fig.1. These cities distribute in each province

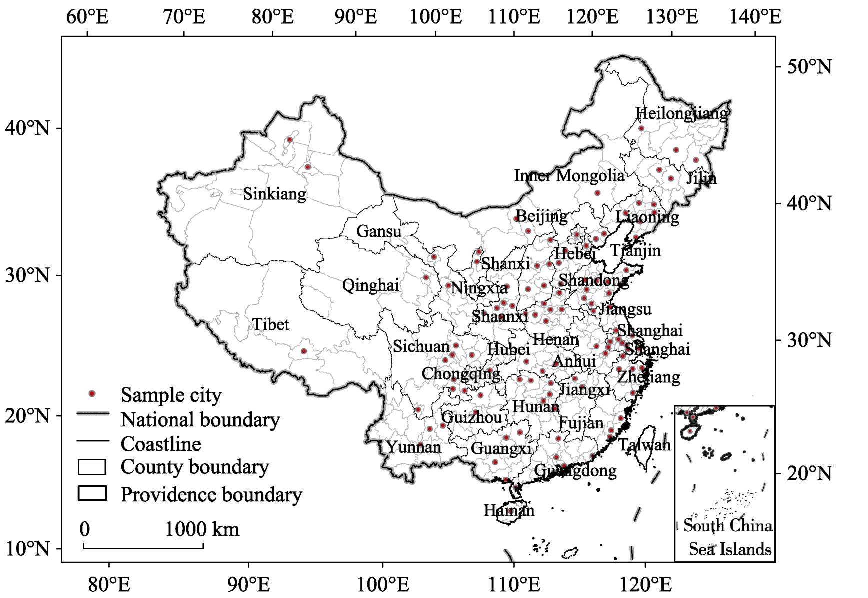

Fig.1 Spatial distribution of sample cities

of China, which can depict air quality at a national scale. We gathered annual air pollutant concentration data of six pollutants in 113 key environmental protection cites throughout China in 2014 and 2015 to explain spatial patterns of urban air pollution.

The MEP's AQI is based on Chinese Ambient Air Quality Standards. In our study, the AQI values of sample cities were obtained from the China's Ministry of Environmental Protection (http://datacenter.mep.gov.cn). Air pollutant data at the city-level were compiled from the China National Environment Monitoring Centre (http://www.cnemc.cn/) and referred to China Statistics Yearbook 2015 and 2016, China Environmental Statistics Yearbook 2014 and 2015. Data related to explain variables in our regression model were collected from the Chinese City Statistical Yearbook 2014 and 2015. Our spatial analysis was conducted in ArcGIS 10 and Geoda.

2.2 Entropy weight method

Urban air quality assessment involved numerous air pollutants. Currently, the AQI is calculated according to concentrations of six criteria pollutants (SO_2, NO_2, CO, O_3, $PM_{2.5}$ and PM_{10}). The AQI issued by MEP is based on the maximum partial concentration among six criteria pollutants. It does not appropriately reflect the overall condition of urban air pollution. In this paper, we use the entropy method to determine the weight of each air pollutant in our assessment of a comprehensive air quality index (CAQI). The entropy method is widely applied in thermodynamics, economic and information from research by Shannon in 1948 (Shannon, 1948). Currently, it is widely used in engineering, economics and finance (Liu *et al*., 2005; Ni *et al*., 2009; Wen-Jie and Shi-Guo, 2008; Zhao *et al*., 2004). The entropy method is used to determine the weight and can provide more useful information (Rubinstein and Kroese, 2008). We supposed there are m pollutants and n cities in this study; steps of the entropy method are as follows:

We noticed that each pollutant was observed at different measurement units. In order to keep all data the same dimension and easier to compare we used the following equation:

$$z_{ij} = (y_{ij} - \min y_i) / (\max y_i - \min y_i) \tag{1}$$

where, z_{ij} refers to the standardized value; y_{ij} refers to the original value of the annual concentration of ith air pollutant of the jth city; $\min y_i$ refers to the minimum value of the data; and $\max y_i$ refers to the maximum of the data.

The entropy of the ith pollutant is defined as:

$$e_i = -k \sum_{j=1}^{n} f_{ij} \times \ln f_{ij} \tag{2}$$

in which: $f_{ij} = z_{ij} / \sum_{j=1}^{n} z_{ij}$, $k = 1/\ln n$, and when $z_{ij} = 0$, $f_{ij} \times \ln f_{ij} = 0$,

The weight of entropy of the ith pollutant is defined as:

$$w_i = (1 - e_i) / \left(m - \sum_{i=1}^{m} e_i \right) \tag{3}$$

in which $0 \leqslant w_i \leqslant 1$, $\sum_{i=1}^{m} w_i = 1$.

Accordingly, $w_i z_i$ denotes the score of ith air pollutant of the jth city, the greater the score of ith air pollutant, the larger contribution to the comprehensive air pollution in the jth city.

To the jth city, its *CAQI* can be computed as follows:

$$CAQI = \sum_{i=1}^{m} w_i z_i \tag{4}$$

2.3 Kenal density estimation

The Kernel density estimation (KDE) calculates the density of features in a neighborhood around those features (Dehnad, 1987). Some researchers have used this method to analyze and detect spatial hotspots of an area (Chu *et al*., 2012; Xie and Yan, 2008). In order to generate a smooth density surface of air pollution concentration, we use KDE to compute pollution density compared with the estimated values. In our research, we adopt KDE to estimate hotspots of each individual pollutant within 113 cities. The general form of a KDE is given as follows (Zhang *et al*., 2013):

$$k(s) = \sum_{l=1}^{n} \frac{1}{\pi r^2} \varphi(d_{ls} / r) \tag{5}$$

where, $k(s)$ is the estimated density at city s; s=1,⋯, 113; r is the search radius (scope) of the KDE; n is the number of sampling cities; d_{ls} is the distance between city l and city s; and φ is the weight function and is usually modeled as a kernel function of the ratio between d_{ls} and r. In this study, we used a kernel with a Gaussian function, and the formula is as follows:

$$\varphi\left(\frac{d_{ls}}{r}\right) = \begin{cases} \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{d_{ls}^2}{2r^2}\right) & \text{if } 0 < d_{ls} \leqslant r \\ 0 & \text{otherwise} \end{cases} \tag{6}$$

2.4 Factors selected affect urban air pollution

By referencing existing literature, we collected eight indicators related to natural and socioeconomic activities (Table 1).

Geographic position determines a region's natural condition, *longitude* (*X*1) and *latitude* (*X*2) are chosen to represent the geographical differences of meteorological condition among cities. Urbanization is along with the spread of urban build-up areas, growth of urban population, development of transportation and changes in lifestyle (Gu *et al*., 2012). Research has demonstrated there is some nexus between urbanization and air pollutant (Liu *et al*., 2017b). Therefore, *urban population density* (*X*3) and *urban built-up area* (*X*4) are selected to describe urbanization variables. Considering industrial emissions contribute significantly to air pollution (Place and Mitloehner, 2010), we chose *industrial SO_2 emissions* (*X*5) and *industrial dust emissions* (*X*6) when measuring industrial emission variables. Clean energy utilization may have a positive effect on air quality, thus the usage amount of *Liquefied Petroleum Gas* (*X*7) is selected. *Electricity consumption per GDP* (*X*8) is a comprehensive index reflecting a city's carbon intensive economy. The variable of *LPG* (*X*7) is expected to have a negative effect on the value of AQI, and other indexes should be positive.

2.5 The regression model

2.5.1 General regression model

To further understand spatial variation in urban air quality across China, the following model (model 1) was constructed to test the relationship between urban air pollutions and various factors:

$$\ln y_i = a_0 + a_1 X1 + a_2 X2 + a_3 \ln X3 + a_4 \ln X4 + \cdots + a_8 \ln X8 + \varepsilon \tag{7}$$

where, the explained variable y is the air pollutant concentration of sampled cities; i represents CAQI or six different pollutants of sampled cities, and they are entered into the model separately; $X1$, ⋯, $X8$ are the explanatory variables listed in Table 1 for observation cities; a [a_0, a_1, ⋯, a_8] are the parameter vectors to be estimated and they reflect the influence of the explanation variables on pollutant concentration among cites; and ε is random disturbance. Considering the influence of heteroscedasticity, we compute the natural logarithm of y and $X3$, $X4$, $X5$, $X6$, $X7$ and $X8$.

2.5.2 Spatial effect models

Given the spatial diffusion effect of air pollution, we argue that air quality of an individual city is partially explained by the air pollutant concentration in nearby or neighboring observations. To test this spillover effect, models including spatial effect should be constructed (Anselin and Griffith, 1988). A spatial lag model (SLM) is a spatial effect model that reflects the influence of spatial area on other adjacent areas in the region. The SLM (model 2) can be defined as follows:

$$\ln y_i = \rho W y_i + a_0 + a_1 X1 + a_2 X2 + a_3 \ln X3 + a_4 \ln X4 + \cdots + a_8 \ln X8 + \varepsilon \tag{8}$$

Table 1 Explanatory variables for regional variation in AQI across China

Category	Indicator	Variable	Expected Sign
Meteorological condition	Longitude	*X*1	+
	Latitude	*X*2	+
Urbanization	Urban population density	*X*3	+
	Urban built-up area	*X*4	+
Industrial emission	Industrial SO_2 emission	*X*5	+
	Industrial dust emission	*X*6	+
Clean energy utilization	LPG (Liquefied Petroleum Gas)	*X*7	–
Carbon intensive economy	Electricity consumption per GDP	*X*8	+

where, y_i, a and X have the same meaning as model 1; ρ is a spatial autocorrelation parameter to be estimated and when the coefficient of ρ is highly significant, the neighborhood spillover effects will be captured. W is a $n \times n$ spatial weight matrix (where n is the number of research cities), where w_{jk} is the spatial weight that links jth and kth cities (with w_{11} = 0). Typically, the definition of neighbors used in the weights matrix is according to distance decay and contiguity effect; ε assumed to be a vector of independent and identically distributed (i.i.d) error terms.

Another model to test the spatial dependence is the spatial error model (SEM), including a spatial autoregressive error term. The SEM model (model 3) is written as:

$$\ln y_i = a_0 + a_1 X1 + a_2 X2 + a_3 \ln X3 + a_4 \ln X4 + \cdots + a_8 \ln X8 + \varepsilon \quad (9)$$

$$\text{in which} \quad \varepsilon = W\varepsilon + \mu \quad (10)$$

where, y_i, a and x have the same meaning as model 1; W is the spatial weights matrix; ε is a vector of spatially auto-correlated error terms; μ is a vector of i.i.d errors; and λ is the spatial autoregressive coefficient to be estimated. If λ is highly significant, it means that pollutant concentration at a certain city is affected by local characteristics and the omitted variables at neighboring cities.

3 Results and analysis

3.1 Overall urban air pollution

Compared with 2014, the annual average concentration of different pollutants in 2015 showed varying degrees of decline (Table 2). Concentrations of PM_{10}, $PM_{2.5}$ and SO_2 had larger magnitudes of decline. The average concentration of PM_{10} decreased from 108.25 to 95.77 and has the biggest change. However, the average concentration of O_3 increased from 135.37–142.73, which has a high amount of increase (7.36). Comparatively, average concentrations of NO_2 and CO have lesser decrease. The main air pollutants of key cities are SO_2, PM_{10} and $PM_{2.5}$, which have a higher concentration.

From the perspective of the entropy weight of each component pollutant, CO and SO_2 contributed a lot to urban air pollution in Chinese cities (Table 3). The total weight of these two pollutants was 0.4873 in 2014 and 0.503 in 2015, reflecting that industrial production has a profound contribution on air pollution. In addition, although O_3 has a higher concentration among the six air pollutants, it has an insignificant influence on air pollution.

3.2 Spatial characteristics of urban air pollution

Fig. 2 illustrates geographical variation of comprehensive air quality. The overall spatial distribution map shows that air quality becomes better in cities of southern China from 2014 to 2015. The change in air quality in cities in Northern China is not significant. However, the distribution of CAQI in the two years shows that there are obvious regional differences of urban air pollution among Chinese cities. Nationally, urban air pollution shows significant North-South differentiation and East-West variation. A dividing line can be drawn along 33N, air pollution in cities located in regions north of that line was more serious than in southern areas. Cities with the worst air quality are mainly concentrated in north and central regions of China, including: (i) the Beijing-Tianjin-Hebei metropolitan areas, (ii) urban agglomeration areas on the Shandong peninsula, (iii) urban agglomeration areas in central Henan, (iv) Shenyang metropolitan areas in Liaoning; and (v) Taiyuan metropolitan areas in Shanxi.

In order to explore different influences of each pollutants, we drew KDE maps with annual average values of different individual pollutants. Fig. 3 shows that urban air pollution

Table 2 Descriptive statistics of six air pollutants of key cities in China

Pollutant	Unite	Year	Min	Max	Mean	Std. dev.	Observations
SO_2	μg m^{-3}	2014	6	123	36.7434	20.3780	113
		2015	5	87	29.2124	16.6639	113
NO_2	μg m^{-3}	2014	14	67	39.2035	10.6429	113
		2015	14	63	37.0442	10.4603	113
PM_{10}	μg m^{-3}	2014	42	224	108.2478	33.5965	113
		2015	40	174	95.7699	30.5424	113
CO	μg m^{-3}	2014	0.9	5.4	2.2858	0.9363	113
		2015	0.9	5.8	2.1708	0.9304	113
O_3	μg m^{-3}	2014	69	209	135.3717	28.2663	113
		2015	72	203	142.7345	24.2196	113
$PM_{2.5}$	μg m^{-3}	2014	23	129	63.9292	19.5493	113
		2015	22	107	56.3982	17.5705	113

Table 3 Entropy weight of each air pollutant in 2014 and 2015

Pollutant	CO	SO_2	PM10	PM2.5	NO_2	O_3
2015	0.2725	0.2305	0.1647	0.1451	0.1212	0.0660
2014	0.2598	0.2275	0.1461	0.1331	0.1172	0.1156

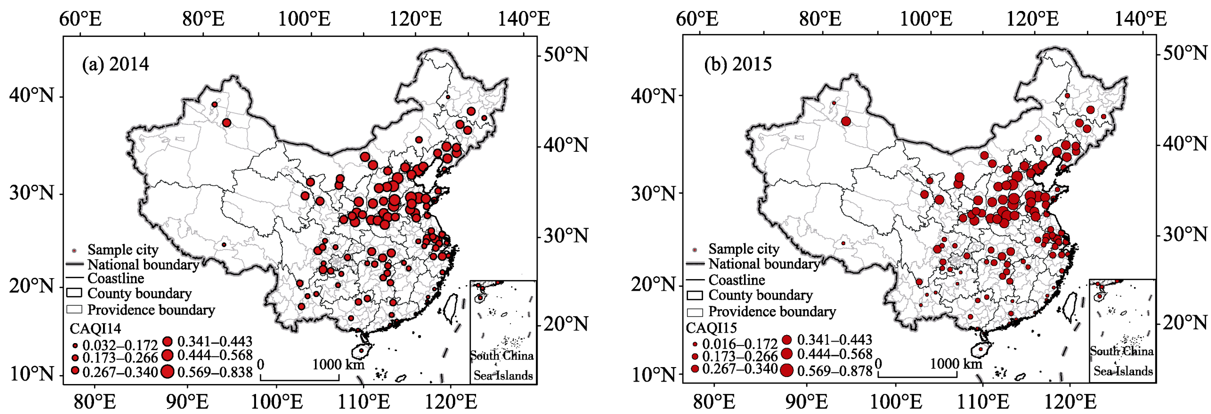

Fig.2 The comprehensive air quality index of sample cities by Entropy-based assessment

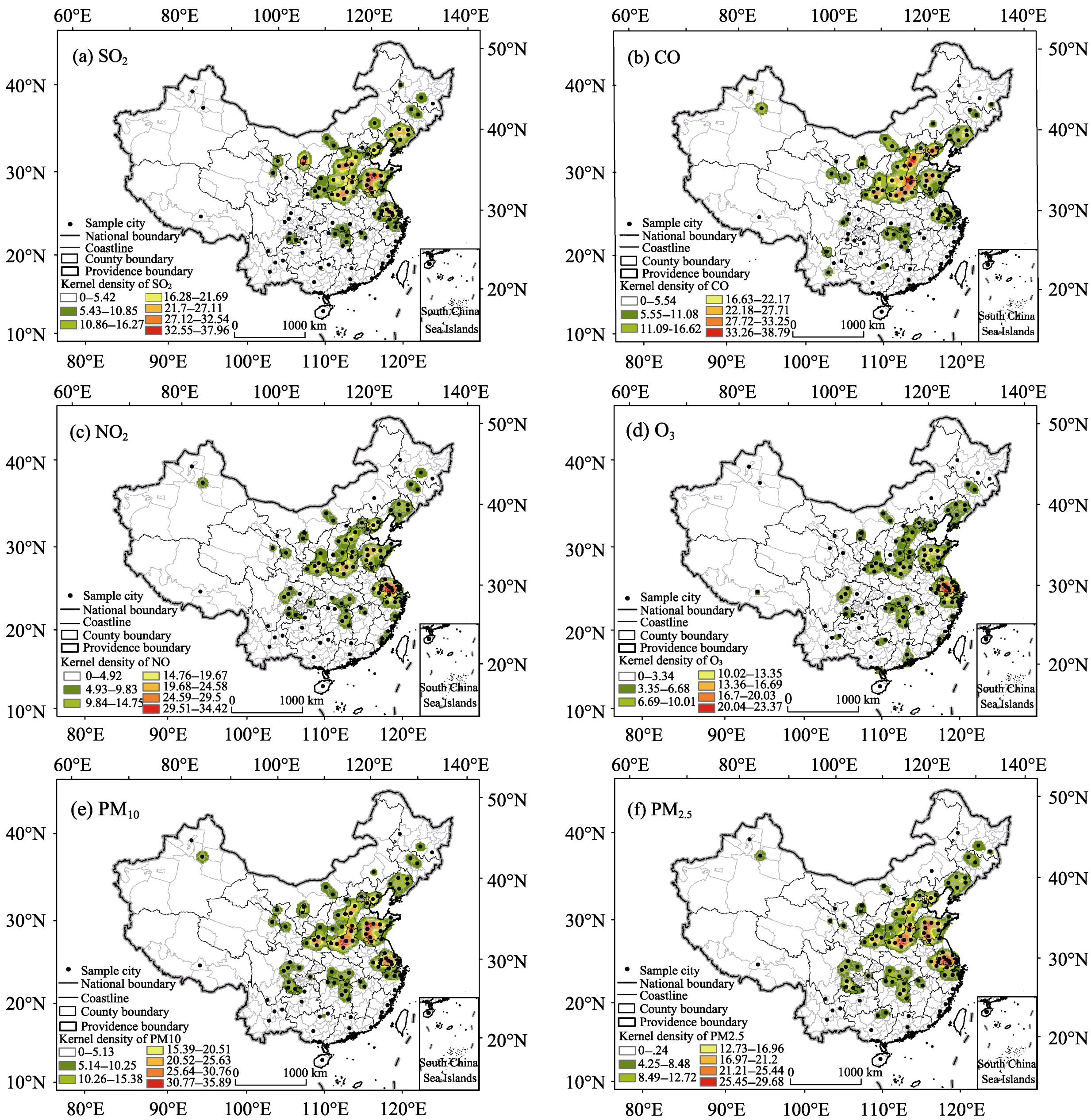

Fig.3 KDE hotspot maps of individual air pollutants in 113 cities of China in 2015

of key cities in China, in general, has evident agglomeration characteristics, but spatial hotspots varied among different individual pollutions.

Hotspots for SO_2 clustered in the middle of the Shandong peninsula, the central region of Henan, and north of Ningxia. The Yangtze River Delta and Shenyang metropolitan areas in Liaoning have slight agglomeration. These regions possess a higher level of industrialization and produced a lot of industrial air pollution. Hotspots for CO clustered in the south of Hebei, north of Henan, and Tianjin. These regions cluster a multitude of people, and the distribution of the population is correlated with transport dust, gas pollution and life pollution emissions.

The spatial hotspot distribution of NO_2 and O_3 is similar, the Yangtze River Delta is the most obvious clustered region and the middle of the Shandong peninsula has slight agglomeration. The hotspots for PM_{10} and $PM_{2.5}$ have similar distributions, whereby the Yangtze River Delta, the middle of Shandong peninsula and the north of Henan are main cluster regions. These regions have obvious clustered characteristics of combined pollutants, where air pollution is affected by multifarious factors. Nationally, hotspots for pollutants are located in Northern China and urban agglomeration areas in the Yangtze River Delta. Most of southern China has good air quality.

From a regional perspective, combined pollutants and secondary pollutants are clustered in development areas, while industrial pollutants are clustered more obviously in industrial cities. NO_2, O_3 and $PM_{2.5}$ are the most obviously clustered pollutants in the Yangtze River Delta. As this region has a high level of economic development, the multitudinous air pollution sources lead to an obvious agglomeration of combined pollutants. CO, $PM_{2.5}$ and PM_{10} are the most obviously clustered pollutants in Beijing-Tianjin- Hebei metropolitan areas and central Henan. Particulate matter is the main pollutant in this region which illustrates the fact that serious haze weather has occurred many times in Northern China. SO_2, PM_{10} and $PM_{2.5}$ are the most obviously clustered pollutants in the urban agglomeration areas on the Shandong peninsula. SO_2 is the most obviously clustered pollutant in the Shenyang metropolitan areas in Liaoning. As Shenyang is an important industrial city in China, the industrial air pollutant SO_2 is the main air pollution source. SO_2 and CO are the most obviously clustered pollutants in the Taiyuan metropolitan areas in Shanxi because Shanxi is the leading coal producing province in China. Rapid mineral exploration and industrial production lead to heavy air pollution. SO_2 is the most obviously clustered pollutant in the Yinchuan metropolitan areas in Ningxia because this region has abundant mineral resources which facilitate the development of industry.

3.3 Factors influencing urban air pollution

In our study, maximum likelihood (ML) techniques were utilized to estimate both a SEM and a SLM. The designed models were run in GeoDa. Table 4 presents the estimated results of the explanatory factors of CAQI. The results show that R^2 of OLS, SEM and SLM is 0.569, 0.652, and 0.658, respectively, which means the SLM is better than the classical multiple linear regression model and SEM. The SLM has the least loglikelihood (–15.820), compared with OLS (–26.088) and SEM (–18.001). At the same time, the AIC (Akaike information criterion) and SC (Schwarz criterion) of this model are lower than the other models. This confirmed that the SLM is a proper alternative model and a region's air quality is influenced by nearby or neighboring air quality. The ρ value of SLM is 0.573 (much larger than zero), which shows a significant neighborhood spillover effect.

The regression model shows that the combination of meteorological factors and human-related determinants greatly influence urban air quality variation in China. The three models almost have the same results, that is, *latitude*, *urban population density* and *industrial dust emission* have a significant positive influence on CAQI, while *Liquefied Petroleum Gas utilization* has a significant negative impact on CAQI. Thereinto, *latitude* has a significance level of 0.01 in the three models, which shows obvious latitudinal variation of air pollution. In other words, air quality of southern China is preferable to that of Northern China. The *urban population density* reflects cities' population aggregation. Additionally, the distribution of the population is correlated with transport dust, gas pollution and life pollution emissions which apparently affect the amount of emissions and the efficiency of diffusion of air pollutants. As industrial emissions are the direct source of air pollution, apparently, industry indicators have significant negative effects on air quality. The *industrial dust emission* has a significance level of 0.1 in SEM and SLM, and at the same time, the coefficient of the *industrial dust emission* is much higher compared with other variables, which confirmed the obvious negative effect of industrial air pollution. In line with expectation, *Liquefied Petroleum Gas utilization* has a negative correlation with the value of CAQI. The *Liquefied Petroleum Gas utilization* has a significance level of 0.05 in OLS and 0.1 in SLM. It shows that clean energy utilization has substantially improved urban air quality.

Tables 5–7 present the estimated coefficients of the explanatory variables of individual air pollutants according to OLS, SEM and SLM, respectively.

The estimation results of the SLM and SEM have confirmed obvious spatial spillover effects of air pollutions among cities in China. The R squared for the six pollutants in the SLM are all higher than in the other models, indicating that this model is better than the classical multiple linear regression models and SEM. Furthermore, the ρ value of SO_2, NO_2, PM_{10}, CO, O_3 and $PM_{2.5}$ produced by the SLM is 0.483, 0.26, 0.623, 0.401, 0.275 and 0.688, respectively. These results are in line with model assumptions, reflecting significant neighborhood spillover effects of air pollution.

Table 4 Estimation results of influencing factors of CAQI in China in 2014

Variable	OLS		SEM		SLM	
	Coefficient	T-value	Coefficient	Z-value	Coefficient	Z-value
CONSTANT	1.094*	1.85	1.444*	1.66	0.251	0.48
*X*1	–0.007	–1.46	–0.008	–1.05	–0.007	–1.54
*X*2	0.034***	5.48	0.035***	3.69	0.015**	2.32
*X*3	0.111**	2.31	0.059	1.29	0.074*	1.77
*X*4	0.072	1.21	0.05	0.96	0.048	0.94
*X*5	0.047	1.01	0.031	0.78	0.029	0.73
*X*6	0.052	1.17	0.068*	1.92	0.072*	1.90
*X*7	–0.067**	–2.27	–0.037	–1.43	–0.043*	–1.68
*X*8	0.127**	2.03	0.092	1.58	0.089	1.64
λ(W)	—	—	0.561***	5.47	0.484***	5.05
R^2	0.569		0.652		0.658	
Adj.R^2	0.536		—		—	
Loglikelihood	–26.088		–18.001		–15.820	
AIC	70.175		54.001		51.639	
SC	94.722		78.548		78.913	

Note: *, **, ***represent significance levels of 0.10, 0.05, and 0.01 respectively. Similarly hereinafter.

Table 5 Estimation results of the influencing factors of air pollutants by OLS

OLS	SO_2		NO_2		PM_{10}		CO		O_3		$PM_{2.5}$	
	Coefficient	T-value	Coefficient	T-value	Coefficient	T-value	Coefficient	T-value	Coefficient	T-value	Coefficient	T-value
Constant	–0.153	–0.22	1.487***	3.59	3.607***	9.02	0.56	0.53	3.331***	8.62	2.696***	5.96
*X*1	0.006	0.97	–0.003	–0.79	–0.007**	–2.03	–0.02***	0.00	0.008**	2.35	–0.001	–0.22
*X*2	0.037***	4.89	0.016***	3.62	0.026***	6.27	0.031***	0.01	–0.003	–0.72	0.017***	3.62
*X*3	0.071	1.24	0.091***	2.71	0.114***	3.51	0.12***	0.04	–0.035	–1.11	0.163***	4.42
*X*4	–0.019	–0.27	0.175***	4.21	0.071*	1.78	–0.12**	0.05	0.098**	2.54	0.081*	1.79
*X*5	0.087	1.57	0.003	0.10	0.008	0.26	–0.007	0.04	0.048	1.59	–0.017	–0.48
*X*6	0.039	0.73	0.033	1.07	0.031	1.02	0.059	0.04	–0.032	–1.09	0.044	1.29
*X*7	–0.091**	–2.55	–0.026	–1.25	–0.072***	–3.57	0.011	0.03	–0.015	–0.79	–0.076***	–3.35
*X*8	0.204***	2.73	0.067	1.54	0.017	0.40	0.132**	0.06	0.112***	2.74	–0.028	–0.58
R^2	0.598		0.511		0.588		0.487		0.187		0.491	
Adj.R^2	0.567		0.473		0.556		0.448		0.124		0.452	

Table 6 Estimation results of the influencing factors of air pollutants by SEM

LMError	SO_2		NO_2		PM_{10}		CO		O_3		$PM_{2.5}$	
	Coefficient	Z-value	Coefficient	Z-value	Coefficient	Z-value	Coefficient	Z-value	Coefficient	Z-value	Coefficient	Z-value
CONSTANT	–0.13	–0.13	1.514***	3.20	3.472***	4.99	0.806	1.16	3.473***	7.92	2.65***	3.11
*X*1	0.006	0.69	–0.003	–0.67	–0.004	–0.64	–0.018***	–3.12	0.007*	1.94	–0.001	–0.11
*X*2	0.035***	3.26	0.016***	3.18	0.02***	2.58	0.03***	4.03	–0.003	–0.61	0.018*	1.90
*X*3	0.061	1.09	0.083**	2.50	0.075***	2.66	0.077*	1.82	–0.036	–1.16	0.101***	3.46
*X*4	–0.028	–0.44	0.16***	4.04	0.048	1.53	–0.085*	–1.74	0.092**	2.49	0.049	1.52
*X*5	0.054	1.13	–0.001	–0.05	0.004	0.17	–0.022	–0.60	0.047*	1.66	–0.018	–0.75
*X*6	0.060	1.38	0.038	1.34	0.028	1.34	0.072**	2.11	–0.031	–1.19	0.044**	2.03
*X*7	–0.056*	–1.79	–0.015	–0.74	–0.031*	–1.94	0.002	0.07	–0.015	–0.84	–0.024	–1.51
*X*8	0.181**	2.56	0.064	1.48	0.026	0.72	0.093*	1.72	0.103**	2.57	–0.005	–0.14
λ	0.529***	4.96	0.27**	2.01	0.709***	8.87	0.441***	3.75	0.259*	1.92	0.783***	11.79
R^2	0.663		0.531		0.727		0.549		0.220		0.723	

Table 7 Estimation results of the influencing factors of air pollutants by SLM

LMLag	SO_2		NO_2		PM_{10}		CO		O_3		$PM_{2.5}$	
	Coefficient	Z-value	Coefficient	Z-value	Coefficient	Z-value	Coefficient	Z-value	Coefficient	Z-value	Coefficient	Z-value
CONSTANT	–0.628	–1.03	0.953**	2.12	1.162***	2.82	0.22	0.46	2.341***	3.75	0.731**	1.99
*X*1	0.004	0.85	–0.005	–1.37	–0.004*	–1.76	–0.013***	–3.10	0.005*	1.75	–0.004	–1.63
*X*2	0.013*	1.71	0.011**	2.56	0.008**	2.12	0.018***	3.02	–0.003	–0.78	0.005	1.51
*X*3	0.043	0.85	0.087***	2.77	0.079***	3.12	0.082**	2.08	–0.034	–1.14	0.11***	4.18
*X*4	–0.043	–0.70	0.16***	4.11	0.051*	1.66	–0.101**	–2.12	0.091**	2.52	0.053*	1.67
*X*5	0.065	1.37	–0.004	–0.12	0.001	0.06	–0.019	–0.52	0.045	1.57	–0.022	–0.89
*X*6	0.058	1.27	0.042	1.44	0.036	1.59	0.073**	2.04	–0.03	–1.11	0.053**	2.23
*X*7	–0.065**	–2.11	–0.016	–0.83	–0.041***	–2.63	0.008	0.35	–0.016	–0.88	–0.034**	–2.11
*X*8	0.166**	2.56	0.053	1.28	0.009	0.29	0.104**	2.06	0.099**	2.58	–0.031	–0.92
W	0.483***	5.17	0.26**	2.26	0.623***	7.89	0.401***	3.73	0.275**	2.12	0.688***	9.73
R^2	0.679		0.539		0.741		0.558		0.228		0.726	

From the perspective of each component pollutant, the variables *latitude* and *electricity consumption per GDP* have a significant positive correlation with the concentration of SO_2, while *LPG* has a significant negative correlation with the concentration of SO_2. This shows that clean energy utilization and a carbon intensive economy have different effects on urban air pollution concentrations of SO_2. Electricity consumption has a close connection with industrial production, which affects the concentration of SO_2. As for NO_2, *latitude*, *urban population density*, and *urban built-up area* have significant positive correlations with NO_2, reflecting that urbanization is a key determinant of the concentration of NO_2. Regarding PM_{10}, urbanization and meteorological conditions have significant positive correlations, while *LPG* has a significant negative correlation with concentration. Urbanization and industrial emissions are principal determinants of $PM_{2.5}$, thereinto *urban population density* is the most significant variable. Meteorological conditions, urbanization, industrial emissions and carbon intensive economy are significantly positively correlated with CO.

4 Conclusions and discussion

Compared with 2014, the annual average concentration of different pollutants in 2015 had varying degrees of decline. The distribution of CAQI shows that there are obvious regional differences in urban air pollution among Chinese cities. Nationally, cities with the worst air quality were mainly located in the northern and central provinces of China, dominantly in Beijing-Tianjin-Hebei metropolitan areas. In general, CO and SO_2 were the two principal pollutants in most Chinese cities, but this varied greatly among cities. The spatial hotspots of air pollutants are mainly located in the Beijing-Tianjin-Hebei metropolitan areas, urban agglomeration areas on the Shandong peninsula, urban agglomeration areas in central Henan, Shenyang metropolitan areas in Liaoning, and Taiyuan metropolitan areas in Shanxi. The regression model showed that industrialization and urbanization factors greatly influenced urban air quality variation in China. The results from the spatial lag regression model confirmed that air pollution has obvious spatial spillover effects among key cities in China. Therein, the high correlation between industrial emission and CAQI shows that industrial emissions are a vital direct source of air pollution. Thus, reducing industrial pollution and strengthening environmental supervision is critical to improving urban air quality. Urbanization has produced much influence on urban air quality because the increasing population has produced more transport dust, gas pollution, and life pollution emissions. This should remind governments to carry out reasonable urban planning to control the size and optimize population distribution. The *Liquefied Petroleum Gas* usage and *electricity consumption* have completely opposite influences on air quality. The results reflect clean energy utilization has the potential to improve urban air conditions, while carbon intensive economy will take much pressure on urban air regulation. Accordingly, government should advocate for the public to have a green life and guide the use of clean energy.

The spatial interdependence effects of urban air quality suggest that Chinese municipal governments should strengthen regional cooperation and deepen bilateral collaboration in terms of air regulation and pollution prevention. The KDE results indicate that cities with severe air quality have obvious agglomeration. It is necessary to construct regional cooperation in environmental governance. As each region has different development policies and resources, their air quality and main air pollutants differ greatly. Thus, different regions should take different management approaches to control air pollution based on their own air conditions and air pollution sources. Technological innovation in clean energy should be promoted and would be expected to reduce emissions of pollutants from related sources.

References

Adams J W, Rodriguez D, Cox R A, 2005. The uptake of so2 on saharan dust: A flow tube study. *Atmospheric Chemistry & Physics Discussions*, 5(10): 2643–2676.

Anselin L, Griffith D A, 1988. Do spatial effecfs really matter in regression analysis? *Papers in Regional Science*, 65(1): 11–34.

Chen D, Liu X, Lang J, *et al*., 2017. Estimating the contribution of regional transport to pm2.5 air pollution in a rural area on the north china plain. *Science of The Total Environment*, 583: 280–291.

Chen W, Tang H, Zhao H, 2015. Urban air quality evaluations under two versions of the national ambient air quality standards of china. *Atmospheric Pollution Research*, 7(1): 49–57.

Chen X, Zhang L-w, Huang J-j, *et al*., 2016. Long-term exposure to urban air pollution and lung cancer mortality: A 12-year cohort study in northern china. *Science of The Total Environment*, 571: 855–861.

Chu H J, Liau C J, Lin C H, *et al*., 2012. Integration of fuzzy cluster analysis and kernel density estimation for tracking typhoon trajectories in the taiwan region. *Expert Systems with Applications*, 39(10): 9451–9457.

Dehnad K, 1987. Density estimation for statistics and data analysis. *Technometrics*, 29(4): 296–297.

Fang C, Wang Z, Xu G, 2016. Spatial-temporal characteristics of pm 2.5 in china: A city-level perspective analysis. *Journal of Geographical Sciences*, 26(11): 1519–1532.

Gu C, Wu L, Lan C, 2012. Progress in research on chinese urbanization. *Frontiers of Architectural Research*, 1(2): 101–149.

Hu J, Ying Q, Wang Y, *et al*., 2015. Characterizing multi-pollutant air pollution in china: Comparison of three air quality indices. *Environment International*, 84: 17–25.

Khanna N, 2000. Measuring environmental quality: An index of pollution. *Ecological Economics*, 35(2): 191–202.

Kyrkilis G, Chaloulakou A, Kassomenos P A, 2007. Development of an aggregate air quality index for an urban mediterranean agglomeration: Relation to potential health effects. *Environment International*, 33(5): 670–676.

Lin X, Wang D, 2016. Spatio-temporal variations and socio-economic driving forces of air quality in chinese cities. *Acta Geographica Sinica*, 71(8): 1357–1371. (in Chinese)

Liu C, Chen R, Zhao Y, *et al*., 2017a. Associations between ambient fine particulate air pollution and hypertension: A nationwide cross-sectional study in china. *Science of The Total Environment*, 584–585: 869–874.

Liu M, Huang Y, Jin Z, *et al*., 2017b. The nexus between urbanization and pm2.5 related mortality in china. *Environmental Pollution*, 227: 15–23.

Liu W, Cai J, Huang C, *et al*., 2016. Associations of gestational and early life exposures to ambient air pollution with childhood atopic eczema in shanghai, china. *Science of The Total Environment*, 572: 34–42.

Liu Z, Jing-Shun D, Wang Q, *et al*., 2005. An evaluation method of scheme based on entropy weight multi-objection decision-making. *Mathematics in Practice & Theory*, 35(10): 114–119. (in Chinese)

Lu X, Han L, 2014. Research on meteorological features of pbl during heavy haze episodes in the city of chengdu, sichuan basin, china. *AGU Fall Meeting*.

Ni J P, Li P, Wei C F, *et al*., 2009. Potentialities evaluation of regional land consolidation based on ahp and entropy weight method. *Transactions of the Chinese Society of Agricultural Engineering*, 25(5): 202–209(208).

Place S E, Mitloehner F M, 2010. Invited review: Contemporary environmental issues: A review of the dairy industry's role in climate change and air quality and the potential of mitigation through improved production efficiency. *Journal of Dairy Science*, 93(8): 3407–3416.

Qin R X, Xiao C, Zhu Y, *et al*., 2017. The interactive effects between high temperature and air pollution on mortality: A time-series analysis in hefei, china. *Science of The Total Environment*, 575: 1530–1537.

Rubinstein R Y, Kroese D P, 2008. The cross-entropy method. *Technometrics*, 50(1): 92–92.

Shannon C E, 1948. A mathematical theory of communiation. *Bell System Technical Journal*, 27(3): 3–55.

Swamee P K, Tyagi A, 1999. Formation of an air pollution index. *Journal of the Air & Waste Management Association*, 49(1): 88.

Tai A P K, Mickley L J, Jacob D J, 2010. Correlations between fine particulate matter ($PM_{2.5}$) and meteorological variables in the united states: Implications for the sensitivity of pm2.5 to climate change. *Atmospheric Environment*, 44(32): 3976–3984.

Wang D, Liu Y, 2016. Spatio-temporal differences and driving forces of air quality in chinese cities. *Journal of Resources and Ecology*, 7(2): 77–84.

Wang F, Peng Y, Jiang C, 2017a. Influence of road patterns on pm2.5 concentrations and the available solutions: The case of beijing city, china. *Sustainability*, 9(2): 217.

Wang N, Lyu X P, Deng X J, *et al*., 2016a. Assessment of regional air quality resulting from emission control in the pearl river delta region, southern china. *Science of The Total Environment*, 573: 1554–1565.

WANG X, GUO X, LANG J, 2016b. Population weighted distribution of $PM_{2.5}$ and PM_{10} in 31 provinces in china. *Ecological Economy*, 32(9): 24–26. (in Chinese)

Wang Z, Ke L, Cui X, *et al*., 2017b. Monitoring environmental quality by sniffing social media. *Sustainability*, 9: 85.

Wen-Jie X U, Shi-Guo X U, 2008. Entropy weight comprehensive health index method for assessment of lake ecosystem health. *Research of Soil & Water Conservation*, 15(1): 126–128. (in Chinese)

WHO, 2012. Mortality and global burden of disease (gbd). *World Health Organisation*.

Xie Z, Yan J, 2008. Kernel density estimation of traffic accidents in a network space. *Computers Environment & Urban Systems*, 32(5): 396–406.

Yang J, Ou C-Q, Song Y-F, *et al*., 2016. Estimating years of life lost from cardiovascular mortality related to air pollution in guangzhou, china. *Science of The Total Environment*, 573: 1566–1572.

Zhang X, Huang P, Sun L, *et al*., 2013. Spatial evolution and locational determinants of high-tech industries in beijing. *Chinese Geographical Science*, 23(2): 249–260.

Zhao D, Zhang Y, Jianfeng M A, 2004. Fuzzy risk assessment of entropy-weight coefficient method applied in network security. *Computer Engineering*, 30(18): 21–23.

Zhou L, Wu J, Jia R, *et al*., 2016. Investigation of temporal-spatial characteristics and underlying risk factors of pmpollution in beijing-tianjin-hebei area. *Research of Environmental Sciences*, 29(4): 483–493. (in Chinese)

中国城市空气污染及其空间溢出效应评估——以113个环保重点城市为例

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摘　要：近年来，中国城市空气污染问题日益受到学界和民众的广泛关注。对城市空气质量进行科学评价并分析其相关影响因素，对于空气污染治理具有重要的理论和实践意义。中国自2013年初实施新的空气质量标准（GB 3095-2012），$PM_{2.5}$，O_3，CO，PM_{10}，SO_2，NO_2等六种污染物被列入监测指标，并由环保部信息发布平台公布污染物浓度数据。本文收集了中国113个环保重点城市2014、2015年六种污染物浓度数据，基于核密度分析法、空间热点分析法来刻画中国城市空气污染演变格局和集聚形势。通过熵值评价系统，构建了综合空气质量（CAQI）指标，并解析六种污染物对中国城市空气质量的综合影响。研究结果表明，大体上，CO和SO_2是中国大部分城市空气的主要污染物，但在不同类型城市表现出明显差异。空气质量较差的城市主要位于华北和华中地区，其中京津冀地区尤为严重。利用一般回归模型、空间滞后和空间误差回归模型探究影响城市空气质量的主要影响因素。结果表明气象条件和人类活动对城市空气质量影响显著，具体表现为工业化和城镇化因子与城市空气综合质量具有较高的相关性。空间滞后模型结果显示城市空气污染存在明显的空间溢出效应，表明临近城市之间的空气质量相互影响程度较高。因此，本研究建议政府和相关组织应加强区域联防联控和深度合作，共同治理城市空气污染问题。

关键词：城市空气质量；熵值法；空间溢出效应；中国