Exploring spatial and temporal distributions of air quality in China from 2013 to 2017

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Abstract. In recent years, severe and persistent air pollution episodes in China have drawn wide public concern. It is necessary to analyse and evaluate the current status of air quality of China, which is significant for sustainable urbanization and environment protection. In this study, we investigate the air quality of the key 74 cities in China from 2013 to 2017 based on the data from the Ministry of Environmental Protection of the People’s Republic of China. With the use of ArcGIS and Stata, we identify the spatial correlation and agglomeration of the air quality. The significant value of Moran’s I test shows positive autocorrelation between the cities and verifies the spatial spill over effect of the air pollution. From the temporal dimension, we find the seasonal variations and an overall better-off trend of air quality. This improvement over the past year benefits from the strict regulations and governance from both central and local government. Our research provides an updated measurement and detailed illustration of the air condition in China. With the exploration of spatial and temporal distributions of air quality, the research findings facilitate the future governance and guidelines for sustainable environmental development.

1. Introduction
During the past decades, China has experienced rapid industrialization and urbanization. The urbanization rate has increased from 17.9% in 1978 to 57.35% in 2016, which means that around 792.98 million people are now living or working in the urban areas in China, according to the data from National Bureau of Statistics of the People’s Republic of China. This notable global event may be one of the greatest human-resettlement experiences in history. This great development has brought unprecedented opportunities to the whole country. It also stimulates the development of several economic industries, like real estate and infrastructures. The Gross Domestic Product (GDP) in China is 11,199.15 billion US dollars in 2016. The GDP value of China represents 18.06% of the world economy and ranks number three all over the world. However, this unprecedented development also brings certain challenges, such as traffic congestion, environment pollution, and unequal social welfare distribution. One of them is the deteriorating air quality. Air pollution has been a severe problem in China, causing huge health damage, social and economic losses for a long time. Many studies have shown that air pollution is a major public health concern for a large part of the world’s population. Considerable evidence has shown that air pollution is linked to a wide range of adverse effects, including harmful health outcomes such as increased mortality and morbidity, economic loss in urban areas, and ecological damage (Chen et al., 2017[1]; Miri et al., 2016[2]).
In recent years, severe and persistent air pollution episodes in China have drawn wide public concern. Many practitioners and scholars have been paying great attention to this research area. Some have investigated the composition, sources, and chemical reactions of the haze-fog pollution, such as Guo, et al. (2010)[3]. Kan, et al. (2009)[4] argue that China faces the worst air pollution problem in the world and outdoor air pollution has become a major concern for public health. Their study raises the public awareness and attention to further research. Some conduct the overall air environment research, Sun, et al. (2012)[5] study the Air Pollution Index in the Pearl River Delta, Yangtze River Delta and Jing-Jin-Ji urban agglomeration from 2001 to 2010. They find that the API of all typical cities have the trend of synchronous development and atmospheric pollution presents regional homogeneous characteristics to a certain extent. Rohde and Muller (2015)[6] apply Kriging interpolation to four months of data for mapping pollution for eastern China. They find that the greatest pollution occurs in the east, but significant levels are widespread across central and northern parts of China. And this impact is not limited to major cities or geologic basins. Their study also points out that the air pollution caused 1.6 million deaths annually which counts for 17% of total annual deaths in China.

Some researchers concentrate on only one specific air pollutant, such as PM$_{2.5}$, Peng, et al. (2016)[7] systematically discuss the spatiotemporal variations of annual average concentrations of PM$_{2.5}$ in China between 1999 and 2011 based on remotely sensed PM$_{2.5}$ data produced by Van Donkelaar et al. in 2015. With the same data source, Li, et al. (2016)[8] analyze the spatiotemporal variations of PM$_{2.5}$ pollution in China from 1998 to 2014. They employ a descriptive statistics method and a Bayesian spatiotemporal hierarchy model with the daily and weekly average PM$_{2.5}$ concentrations in 338 cities in China to explore its spatial-temporal patterns. They find that the city level PM$_{2.5}$ shows a significant seasonal cycle with heavy pollution from October to following April, while the other months are usually better. Some other research has focused on various single pollutant, such as SO$_2$, PM$_{10}$, NO$_2$, CO and O$_3$ (Johansson, et al., 2007[9]; Karar and Gupta, 2006[10]; Rooney, et al., 2012[11]). A few researchers has been interested in O$_3$ as the influence is getting severe and the formation is difficult to identify, such as Zhang, et al.(2007)[12], Sun, et al.(2017)[13], etc. The formation of haze-fog was closely linked to atmospheric and meteorological conditions (Li, et al., 2013[14]), but the formation is more complicated for O$_3$. Therefore, even these single-pollutant researches may provide us with some information with PM$_{2.5}$ or O$_3$, a comprehensive and systematically perspective may better explore our knowledge and understanding of the air environment.

From the above literature review, we can see that air quality has drawn much attention in recent years. However, there may still remain some research gap. Previous studies on air environment in China have focused on relatively restricted geographical areas or were limited to short periods. Due to the vastness of China, air pollution may vary in different districts and periods. In this research, we are going to take a more general and a macro perspective. This study aims to investigate the spatial and temporal distributions of the air quality on a national scale in China from 2013 to 2017, and the research targets are the main 74 cities listed in the statistical monthly report provided by Ministry of Environmental Protection of the People’s Republic of China.

This rest of the paper is organized as follows. Section 2 presents the data sources and the calculation process of the air quality index. Section 3 describes the spatial distribution and measures the spatial autocorrelation of the air quality between these 74 cities. Section 4 focuses on the temporal relationship and change within the period from 2013 to 2017. Section 5 discusses the main findings, the conclusions and the future potential research areas.

2. Data sources and data processing
Air Quality Composite Index is used for this study. This data is got from the website of Ministry of Environmental Protection of the People’s Republic of China. In this study, we analysed the corresponding data of 74 capital cities, main urban agglomerations, municipalities and other key cites in mainland China. The original data is from monthly report, and we calculated the average index value from 2013-2017 to stand for the air status of each specific city.

Firstly, we will introduce the calculation process of this official Air Quality Composite Index. It is used to measure the overall air quality of the urban environment in China. The index synthesizes SO$_2$,
NO$_2$, PM$_{10}$, PM$_{2.5}$, CO and O$_3$ information into a comprehensive value. The larger the index, the severer the air pollution is. The detailed measurement and calculation process are as following:

(1) Calculate the statistical concentration of each pollutant
Calculate the monthly concentration of SO$_2$, NO$_2$, PM$_{10}$, PM$_{2.5}$, the ninety-fifth percentile of the daily average value of CO, and the ninetieth percentile of the daily maximum 8 hour average of O$_3$. If the overall number of days cannot meet the requirement of the percentile calculation, the maximum value of everyday will be selected.

(2) Calculate the monomial quality index of each pollutant
The monomial quality index of pollutant $i$ is measured with:

\[ I_i = \frac{C_i}{S_i} \]  

Where, $I_i$ is the concentration of pollutant $i$. When $i$ is SO$_2$, NO$_2$, PM$_{10}$ or PM$_{2.5}$, $C_i$ is the monthly average value. When $i$ is CO or O$_3$, $C_i$ is the concentration of specific percentile value, $S_i$ is the level two standard of pollutant.

(3) Calculate the annual (seasonally or monthly) composite index of air quality $I_{sum}$
The measurement of the air quality composite index should contain all the six pollutants and is measured as:

\[ I_{sum} = \sum I_i \]  

Where, $I_{sum}$ is the air quality composite index, $I_i$ is the monomial quality index of pollutant $i$ (SO$_2$, NO$_2$, PM$_{10}$, PM$_{2.5}$, CO and O$_3$).

The concentration limit of the six pollutants is regulated in Ambient Air Quality Standard (GB3095-2012), as shown in Table 1.

Table 1. The concentration limits for each pollutant

| Pollutant | Measurement Period | Pollutant Concentration Limit | Unit |
|-----------|--------------------|------------------------------|------|
|           |                    | Level 1 | Level 2 |      |
| SO$_2$    | Annual             | 20      | 60      | μg/m$^3$ |
|           | Daily              | 50      | 150     |       |
|           | Hourly             | 150     | 500     |       |
|           | Annual             | 40      | 40      |       |
| NO$_2$    | Daily              | 80      | 80      |       |
|           | Hourly             | 200     | 200     |       |
| CO        | Daily              | 4       | 4       | mg/m$^3$ |
|           | Hourly             | 10      | 10      |       |
| O$_3$     | Average within 8 hours | 100 | 160 | μg/m$^3$ |
|           | Hourly             | 160     | 200     |       |
| PM$_{10}$ | Annual             | 40      | 70      |       |
|           | Daily              | 50      | 150     |       |
| PM$_{2.5}$| Annual             | 15      | 35      |       |
|           | Daily              | 35      | 75      |       |

3. Spatial distribution of air quality during 2013-2017

3.1. Visualization air quality distribution
After collecting the monthly air quality index of all the 74 cities from 2013 to 2017, we calculated the average index of each city and presented them in a map with the use of ArcGIS. The original data is from 2013 to 2017, except for the missing data of July 2013 and December 2016. We use the average value of the two adjacent month index to stand for those two missing month data. This provides us a direct and visualized way to identify the spatial variations of the air quality among different cities.

From Figure 1, we can see that those 74 key cities can mainly be clustered into four types based on the interval, and the details can be seen from Table 2.
Figure 1. Mapping of the average air quality index in China

Table 2. Classification of the 74 cities

| Clusters | Number | Cities |
|----------|--------|--------|
| Tier 1   | 13     | Haikou, Zhoushan, Lhasa, Fuzhou, Huizhou, Xiamen, Zhuhai, Shenzhen, Lishui, Kunming, Taizhou, Zhongshan, Guiyang |
|          |        | Jiangmen, Nanning, Dongguan, Zhangjiakou, Zhaoping, Ningbo, Quzhou, Dalian, Guangzhou, Wenzhou, Foshan, Yancheng, Nanchang, Shanghai, Jinhua, Chengde, Jiaxing, Chongqing, Hohhot, Huzhou, Nantong, Lianyungang, Shaoying, Changsha, Huaian, Qingdao, Hangzhou, Suzhou, Taizhou, Yangzhou, Hefei, Suqian, Zhenjiang, Xining, Wuxi, Changzhou, Changchun, Nanjing, Urumchi, Harbin, Qinghuangdao, Wuhan, Yinchuan, Lanzhou, Chengdu |
| Tier 2   | 45     | Xuzhou, Beijing, Shenyang, Cangzhou, Tianjin, Xi'an, Taiyuan, Langfang, Zhengzhou, Ji'nan, Hengshui |
| Tier 3   | 11     | Tangshan, Handan, Shijiazhuang, Baoding, Xingtai |
| Tier 4   | 5      |               |

The lowest air quality index means the least pollution and the best air environment, so we cluster those cities with lowest air quality index into tier 1. For instance, Haikou is quite famous for the good and healthy air. It usually ranks the number 1 in either monthly or annual rankings provided by Ministry of Environmental Protection. This is benefited from the locational advantages which is part of the southern coastal. Moreover, the trend of the perennial wind is the southeast wind and the northeast wind, and this will help the air cross-ventilation. Tier 2 is the largest group which contains 45 cities altogether. This means that the majority Chinese cities are in the median condition. Tier 3 cities are located in the middle or norther part and the air quality there is not quite satisfactory. Those 5 cities in Tier 4 are with the highest air quality index, which means they suffer from severe air pollution. Take Xingtai for example, the serious problem can be attributed to three reasons. One is low terrain and low wind speed which is not conducive to the diffusion of pollutants (Liang, et al., 2015[15]). Another reason is the long duration of haze and the large size of affected area. Special climate conditions have resulted in a long period of accumulation of atmospheric pollutants, which aggravates the pollution. The third reason is because there is too much emission and heavy pollution by the enterprises or
factories. There are more than 100 coal-fired enterprises distributed in Xingtai with more than 10 million tons annual production, far exceeding the environmental capacity of the city.

On the other hand, we can also identify the existence of spatial aggregation of the air quality among the cities. Firstly, the air quality in China varies greatly across the whole study area. Air quality in southern part is clearly better than that in the northern area which is consistent with the findings of some previous studies performed in China (Zhan, et al., 2017[16]). Secondly, the adjacent cities tend to have more similar air quality cluster than with the other remote cities. This is because the air is boundless and the air pollution is not only restricted in one specific city. The air condition will easily be affected by the neighborhood. It is rational that this impact is bigger in the adjacent areas than that in the far-away areas. Moreover, as seen in the figure, for the most polluted areas, a pronounced spatially concentrated trend is observed when compared with other status. This means that the higher air quality index cities locate more concentrated around Bohai Rim region and Jing-Jin-Ji urban agglomeration. The lower index cities spread in a broader region and this can also be attributed to the sample bias.

3.2. Moran’s I test

According to Tobler’s First Law of Geography, everything is related to everything else, but near things are more related than distant things (Tobler, 2004[17]). Ignoring the spatial effects would lead to biased analysis and inconsistent parameter estimates (Anselin and Bera, 1998[18]). The widely used methods for testing spatial effect is Moran’s I test (Moran, 1950[19]). Moran’s I test is developed as a measurement of spatial autocorrelation which is multi-dimensional and multi-directional. It is a product of moment coefficient which can be divided into global and local levels, and the global Moran’s I test is defined as:

\[
l = \frac{n}{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n}(x_i - \bar{x})^2}
\]

Where \( n \) is the number of samples of the study which is 74, \( w_{ij} \) indicates the spatial weight between city \( i \) and \( j \), \( x_i, x_j \) is the observation variable which is the air quality index at city \( i, j \). The value of Moran’s I vary from -1 to 1. Negative values illustrate negative spatial autocorrelation, whereas positive result illustrates positive autocorrelation and a zero value illustrates random spatial autocorrelation. For testing statistical hypotheses, we can transform the Moran’s I value to Z-scores. When the Z value is greater than 1.96 or smaller than -1.96, the spatial autocorrelation is significant at the 95% confidence level.

In some cases, the overall evaluation might ignore the atypical characteristics of regional areas. We introduce Local Moran’s I (LISA) as follows to examine whether there is significant agglomeration phenomenon of local areas. While for this study, because we are not going to focus on the different areas, only the global Moran’s I test will be conducted. (In fact, we have estimated the local Moran Index, which is not released here. If interested, please ask the author).

\[
l_i = \frac{x_i - \bar{x}}{s^2} \sum_{j=1}^{n} w_{ij}(x_j - \bar{x})
\]

\[
S^2 = \frac{\sum_{i=1}^{n} x_i^2}{n} - \bar{x}^2
\]

\[
\bar{x} = \frac{1}{n} \sum_{i=1}^{n} x_i
\]

Where \( n \) is the number of samples which is 74 in this study, \( w_{ij} \) indicates the spatial weight between city \( i \) and \( j \), \( x_i, x_j \) is the observation variable at location \( i, j \) and \( \bar{x} \) is the average of all the sample value. Spatial weight matrix shows the spatial dependence among the variables. Different ways for spatial weight matrix specification may be possible and there is little formal guidance on how to choose the right spatial weight. It is associated with the autoregressive process of the variables and is supposed to be exogenous. It is because that this \( n \times n \) dimensional \( W \) contains exogenous information between the spatial correlations between location \( i \) and location \( j \). The values of the spatial weight matrix is determined before or separated from the estimation process of the model coefficients. \( W \) can be shown as:
The diagonal elements of \( W \) is defined to be zero, while \( w_{ij} \) can be measured in certain ways. \( w_{ij} \) typically refers to the spatial influence of unit \( j \) on unit \( i \). To reduce the exogenous influence of the locations, the weight matrix is usually row-standard, such as \( \sum w_{ij} = 1 \). Normally there are several ways to estimate the weights and we will classify them into two categories.

In this study, the weight of city \( i \) and city \( j \) is displayed as \( w_{ij} \) and measured in the reversed distance of those two cities with the use of their coordinates. Because the city is a large area, we chose the coordinates of each city’s municipal government to stand for the geographical location of a city. We set the spatial weight matrix by using the rules shown in the following equation 9:

\[
W = \begin{bmatrix}
    w_{11} & w_{12} & \cdots & w_{1n} \\
    w_{21} & w_{22} & \cdots & w_{2n} \\
    \vdots & \vdots & \ddots & \vdots \\
    w_{n1} & w_{n2} & \cdots & w_{nn}
\end{bmatrix}
\]  

(8)

From Table 3, we can see that the value of global ‘morani’ is 0.357, which means the spatial autocorrelation of the air quality in different cities exists. And the value of ‘probability’ is 0.000 which shows that the spatial autocorrelation differs significantly from zero at the 1% level of significance. Then the hypothesis of no spatial dependence exists is rejected. We identify the existence of spatial autocorrelation of the air quality among the 74 cities. From both the visualization of the map and the quantitative analysis, we verify the strong spatial correlation of the air qualities among different cities.

### Table 3. Measure of global spatial autocorrelation

| Weights Matrix |  |
|----------------|---|
| Name: W |  |
| Type: Distance-based (inverse distance) |  |
| Distance Band: 0.0< d <=15.0 |  |
| Row-standardized: Yes |  |
| Moran's I |  |
| Variables | I | E(I) | sd(I) | z | p-value* |
| Value | 0.357 | -0.014 | 0.030 | 12.271 | 0.000 |

* 1-tail test

### 3.3. Moran’s I scatterplot

We further constructed Moran’s I scatterplot based on the data of each year from 2013 to 2017, to see the variations between the yearly distribution. The following Figure 2 shows the Moran index of the 74 cities within the five years. As shown in the figures, the Moran’s I index of most cities fall in the first and third quadrants which are H-H or L-L clusters, and a few in the second quadrant. This represents the existence of positive or negative correlations of air quality in most cities. In case of 2013, most cities tend to be spatial homogenous which means that high index is always surrounded by high index city, vice versa. Only 5 cities are in the second quadrant where stands for heterogeneity. The number 54 (Urumchi) is the most unusual dot observed from figure. This may due to its specific geographical location or result from the natural bias of the cities selected in this study. As seen from 2013, majority cities present spatial autocorrelation, a few tends to be heterogeneous. Similar findings can be found in the other 4 years, except for some minor fluctuation.
4. Temporal change of air quality during 2013-2017

Except for the geographical variations of the air quality in different cities, there are also changes over the time. Two obvious characteristics can be seen from the following Figure 3. One is the overall air quality index has a declining tendency from 2013 to 2017, especially for the annual highest index. We can see that the peak of air quality index decreases from 11 in 2013 to 9 in 2014, and finally to 7 in the end of 2017. As the lower the index, the better the air is. This means the air environment has been improved during the past years. This improvement benefits from the endeavour of both the public sectors and the private sectors. Especially from the perspective of public sectors, the Chinese Government has attached great importance to controlling and alleviating air pollution through a series of regulatory policies in recent years.
Another trend is seasonal fluctuations. It can be seen that the air quality index present a U-shaped variation over the months, with the highest levels in the winter months (December or January) and the lowest levels in the summer months (August or September). One reason is because the widely use of coal in winter. The main sources of air pollution in China are heating emission, motor vehicle emission, industrial emission and wind sand weather (Zang, et al., 2015[20]). Especially for the heating, coal is the main material and accounts for about 70% of the nation’s energy consumption. Coal-fired heating will lead to the increase of sulphur dioxide and dust particles in the air. With the low temperature, low wind and other meteorological conditions in winter, haze is easy to accumulate and lead to prolonged air pollution. Another reason is the poor facilities and technology. The technology and manufacturing level of all kinds of combustion equipment are low, and the utilization rate of energy is not high. Many coal-fired boilers have no installation of environmental protection equipment, so the smoke after burning directly spread into the air. Therefore, the air quality is usually worse in the winter period.

5. Discussions and conclusions

In this study, we take a more general and a macro perspective to investigate the spatial and temporal distributions of the air quality on a national scale in China from 2013 to 2017 based on the data of key 74 cities listed in the statistical monthly report provided by Ministry of Environmental Protection of the People’s Republic of China. From the spatial dimension, the significant value of Moran’s I test shows positive autocorrelation between the cities and testify the spatial spillover effect of the air pollution. Our findings show that the air quality of southern cities is relatively better than that of the northern cities, but the gap has been narrowing with time. Moreover, air pollution has a spatial clustering trend, with high pollutions areas located near each other. From the temporal dimension, we find seasonal variation with the highest levels in the winter months and the lowest levels in the summer months. There is also an improving tendency of the air quality that the overall index gets smaller and smaller from 2013 to 2017. This better-off over the past years benefits from the strict regulations and governance of both central and local government. In recent years, the Chinese Government has attached great importance to controlling and alleviating air pollution through a series of regulatory policies, such as the third National Ambient Air Quality Standard, the Ten Specific Measures of Air Pollution Prevention and Control Action Plan, etc. This research provides an updated measurement and detailed illustration of the air condition in China.

With the exploration of spatial and temporal distributions, the research findings facilitate the future governance and sustainable environment development to some extent. However, because of the limited sample size, there remain some research limitations. The future research can explore this research area with the availability of more samples, while adopting the methods used in this study.

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